Deployment of Privacy-Preserving Machine Learning for Political Polling in the 2024 Presidential Election

Sam Buxbaum

Lucas M. Tassis, Lucas Boschelli, Giovanni Comarela, Mayank Varia, Mark Crovella, Dino P. Christenson

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WashU

PPML Workshop

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Traditional Political Polling

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West Virginia 2024 Presidential Election Polls

Harris vs. Trump

Source	Date	Sample	Harris	Trump	Other
Research America	8/30/2024	400 LV ±4.9%	34%	61%	5%

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Michigan 2024 Presidential Election Polls

Instantly compare a poll to prior one by same pollster

Harris vs. Trump

Source	Date	Sample	Harris	Trump	Other
Average of 23 Polls†			48.6%	46.8%	-
FAU / Mainstreet	11/04/2024	713 LV	49%	47%	4%
Emerson College	11/04/2024	790 LV ±3.4%	50%	48%	2%
Research Co.	11/04/2024	450 LV ±4.6%	49%	47%	4%
InsiderAdvantage	11/03/2024	800 LV ±3.7%	47%	47%	6%
Trafalgar Group	11/03/2024	1,079 LV ±2.9%	47%	48%	5%
MIRS / Mich. News Source	11/03/2024	585 LV ±4%	50%	48%	2%
NY Times / Siena College	11/03/2024	998 LV ±3.7%	47%	47%	6%
Morning Consult	11/03/2024	1,108 LV ±3%	49%	48%	3%
AtlasIntel	11/02/2024	1,198 LV ±3%	48%	50%	2%
Redfield & Wilton	11/01/2024	1,731 LV ±2.2%	47%	47%	6%
The Times (UK) / YouGov	11/01/2024	942 LV ±3.9%	48%	45%	7%
EPIC-MRA	11/01/2024	600 LV ±4%	48%	45%	7%
Marist Poll	11/01/2024	1,214 LV ±3.5%	51%	48%	1%
AtlasIntel	10/31/2024	1,136 LV ±3%	49%	49%	2%
Echelon Insights	10/31/2024	600 LV ±4.4%	48%	48%	4%
MIRS / Mich. News Source	10/31/2024	1,117 LV ±2.5%	47%	49%	4%
UMass Lowell	10/31/2024	600 LV ±4.5%	49%	45%	6%
Washington Post	10/31/2024	1,003 LV ±3.7%	47%	46%	7%
Fox News	10/30/2024	988 LV ±3%	49%	49%	2%
CNN	10/30/2024	726 LV ±4.7%	48%	43%	9%
Suffolk University	10/30/2024	500 LV ±4.4%	47%	47%	6%

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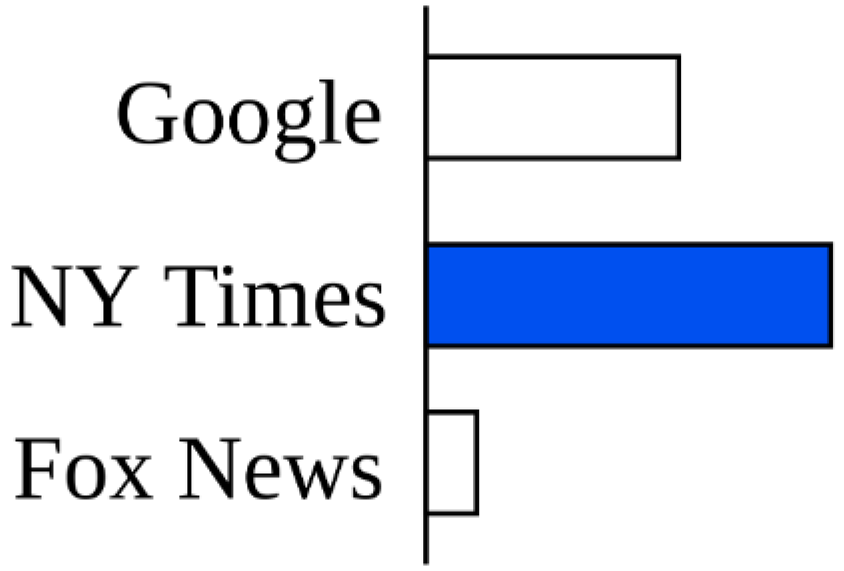

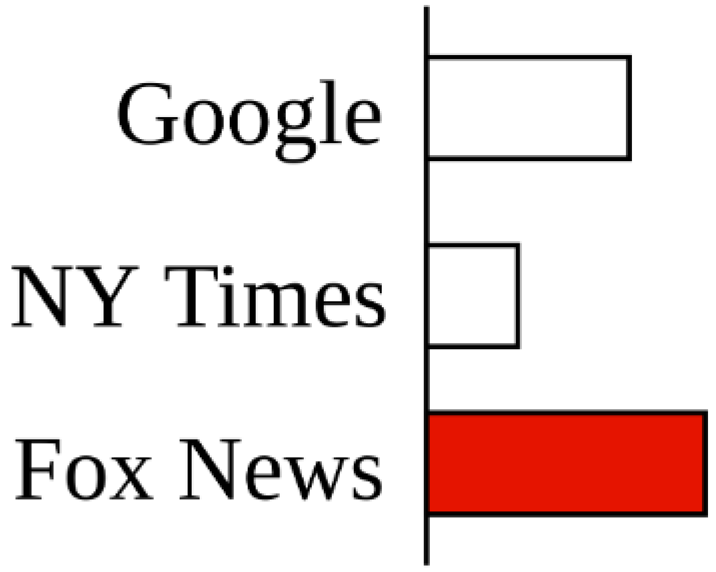

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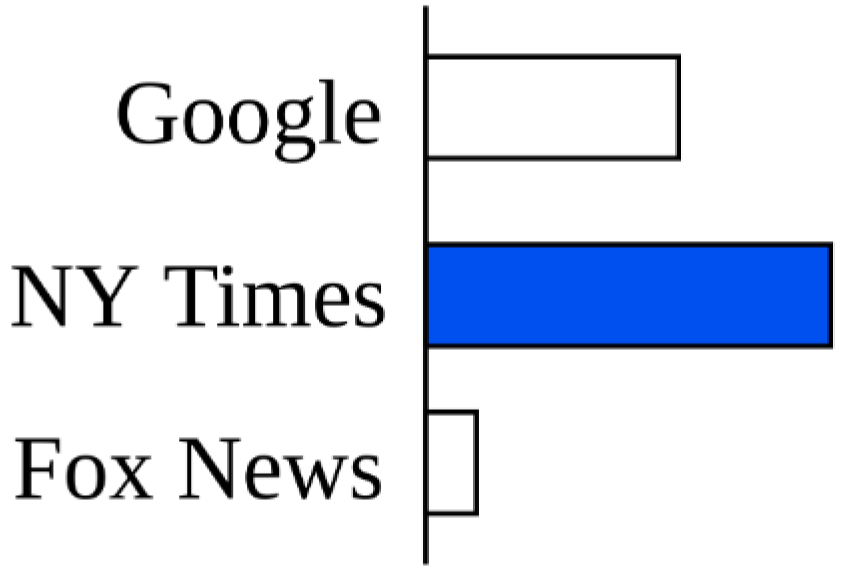
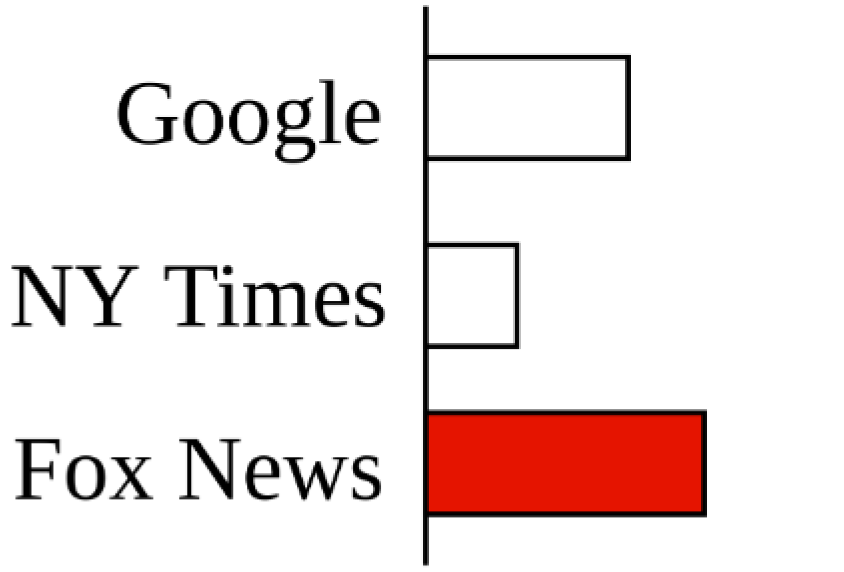
- More data





Web Browsing for Political Polling

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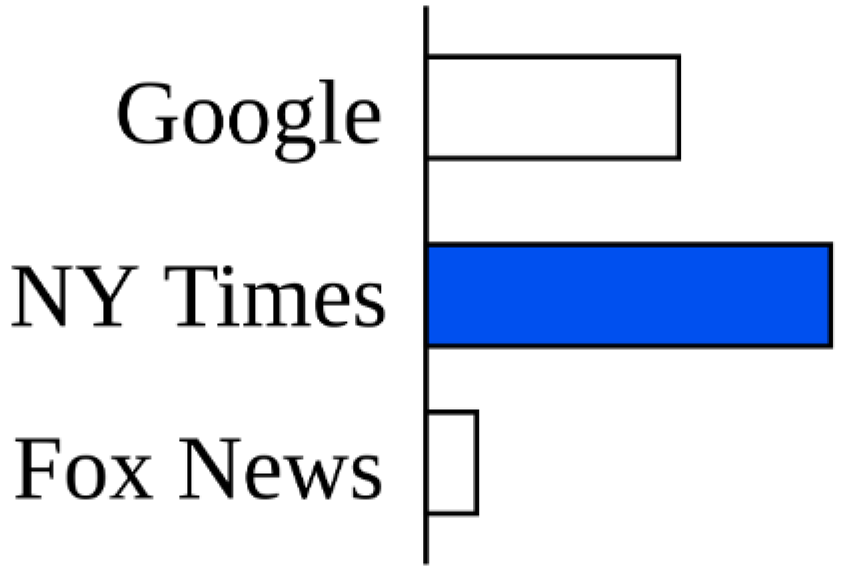
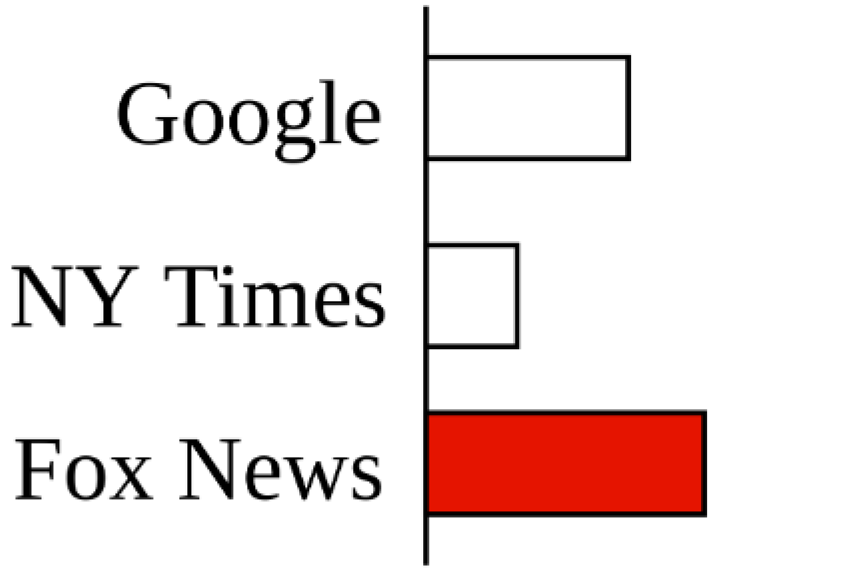
- More data
- Fully automated





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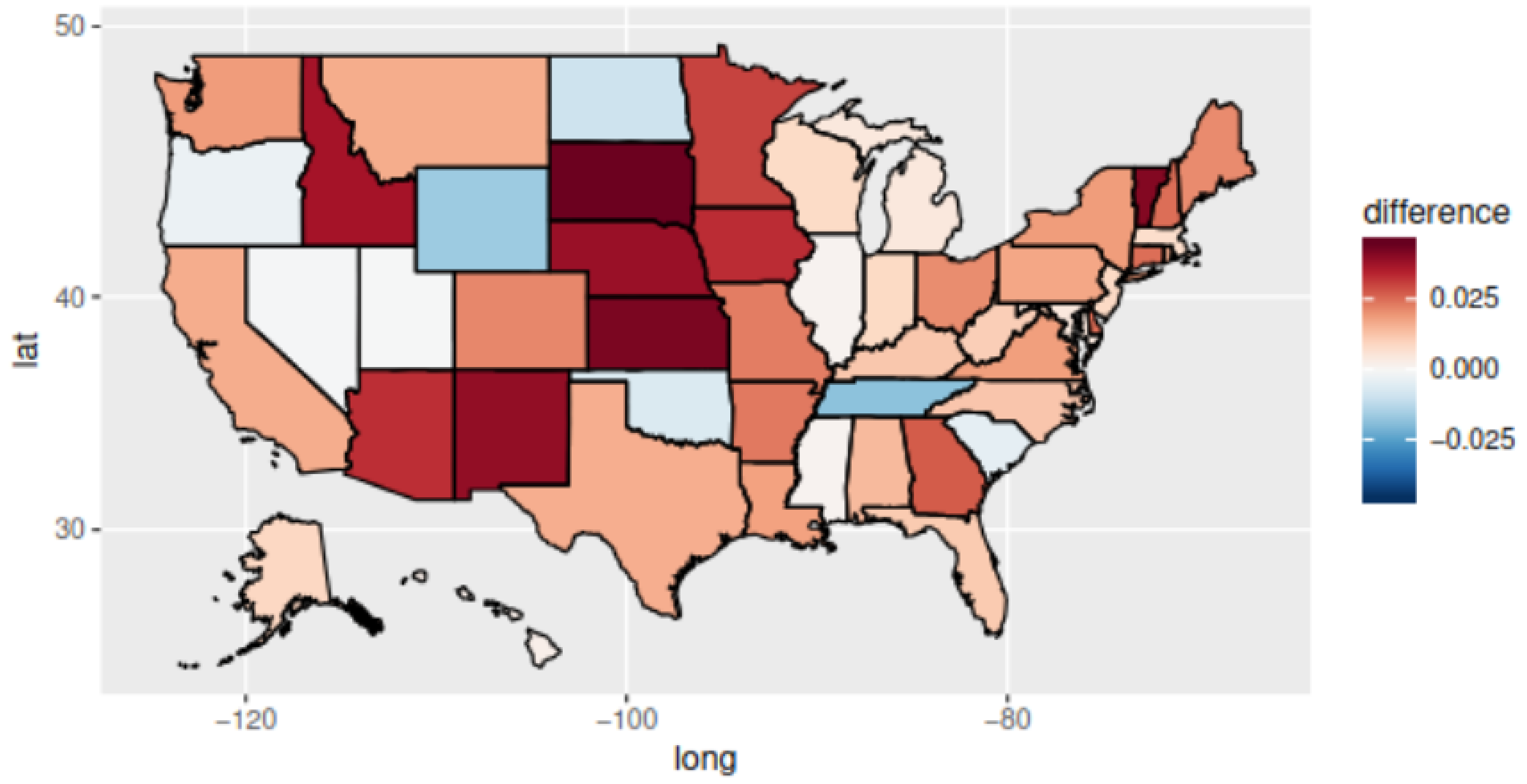
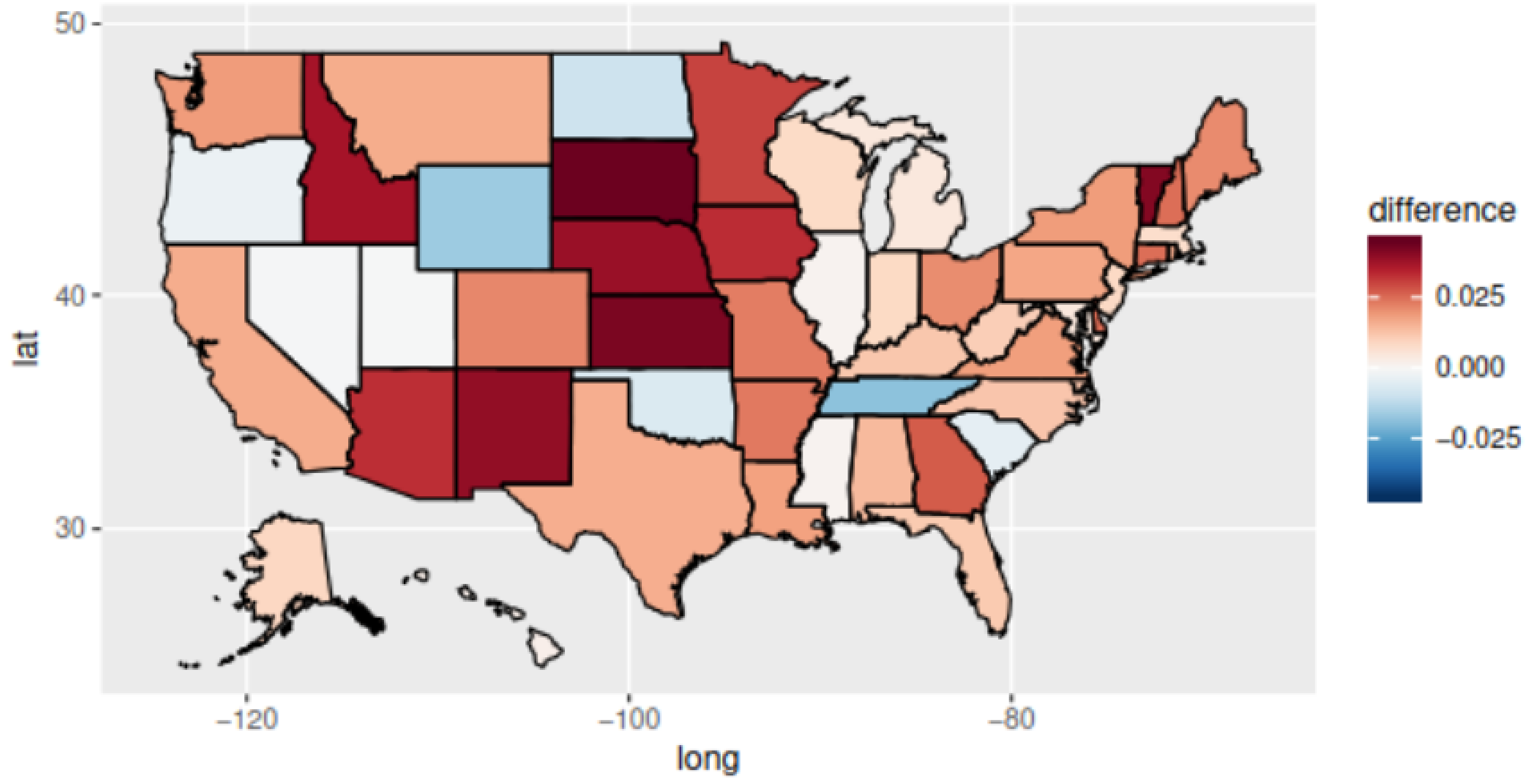


Figure 8: Impact of the 'Comey letter' at the state level.

Prior Work

- Web browsing behavior can predict voting results
- Quantifying the 'Comey letter' (Comarela et al.)
- Social media referrals are the best signal



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Two Approaches to Political Polling

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- Slow
- Expensive
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VS

Web Behavior Analysis

- Immediate
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Two Approaches to Political Polling

Traditional Polling		Web Behavior Analysis
Slow	VS	Immediate
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What about privacy?

Our Contributions

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- All analysis took place under MPC

Learning from Label Proportions (LLP)

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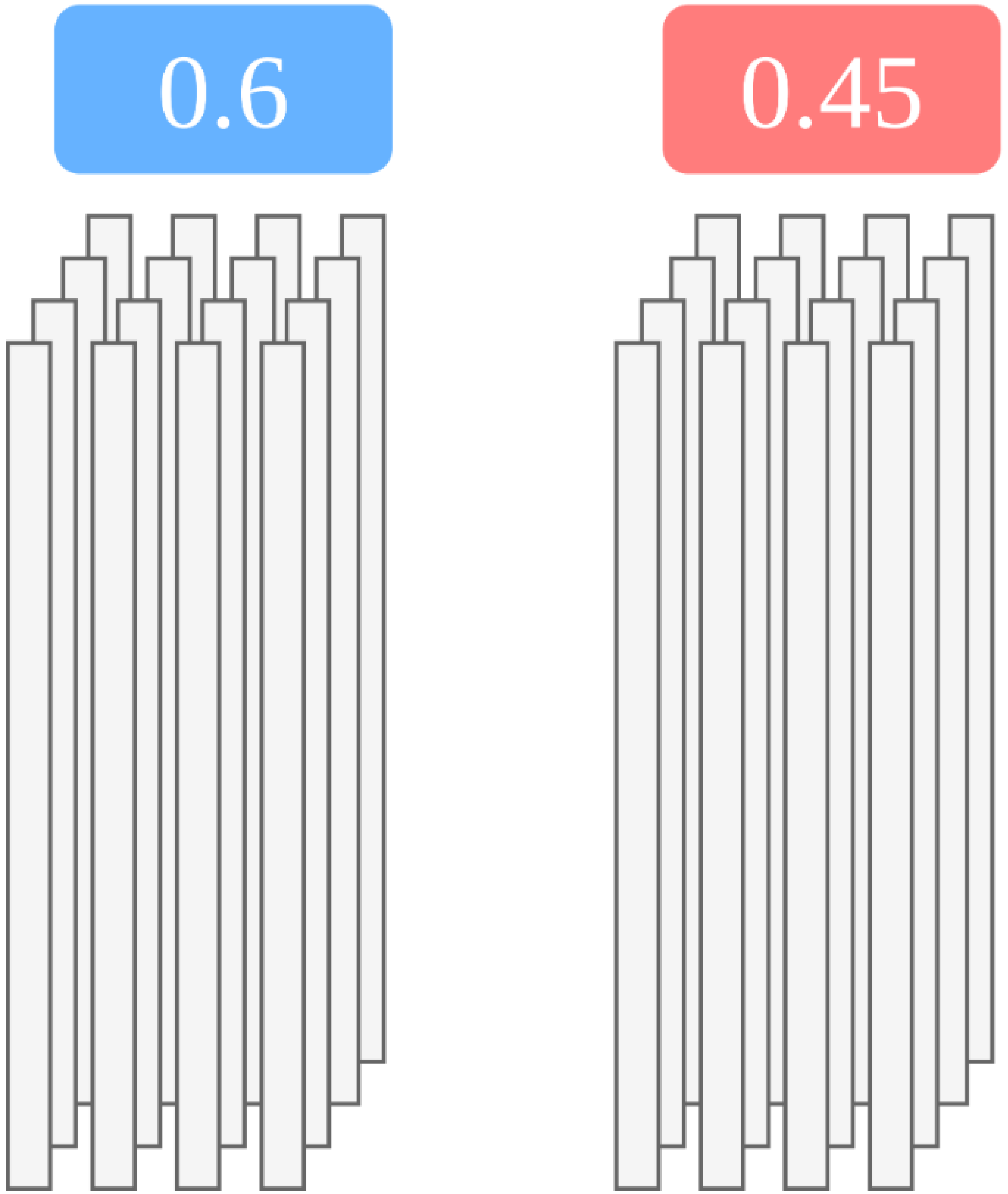

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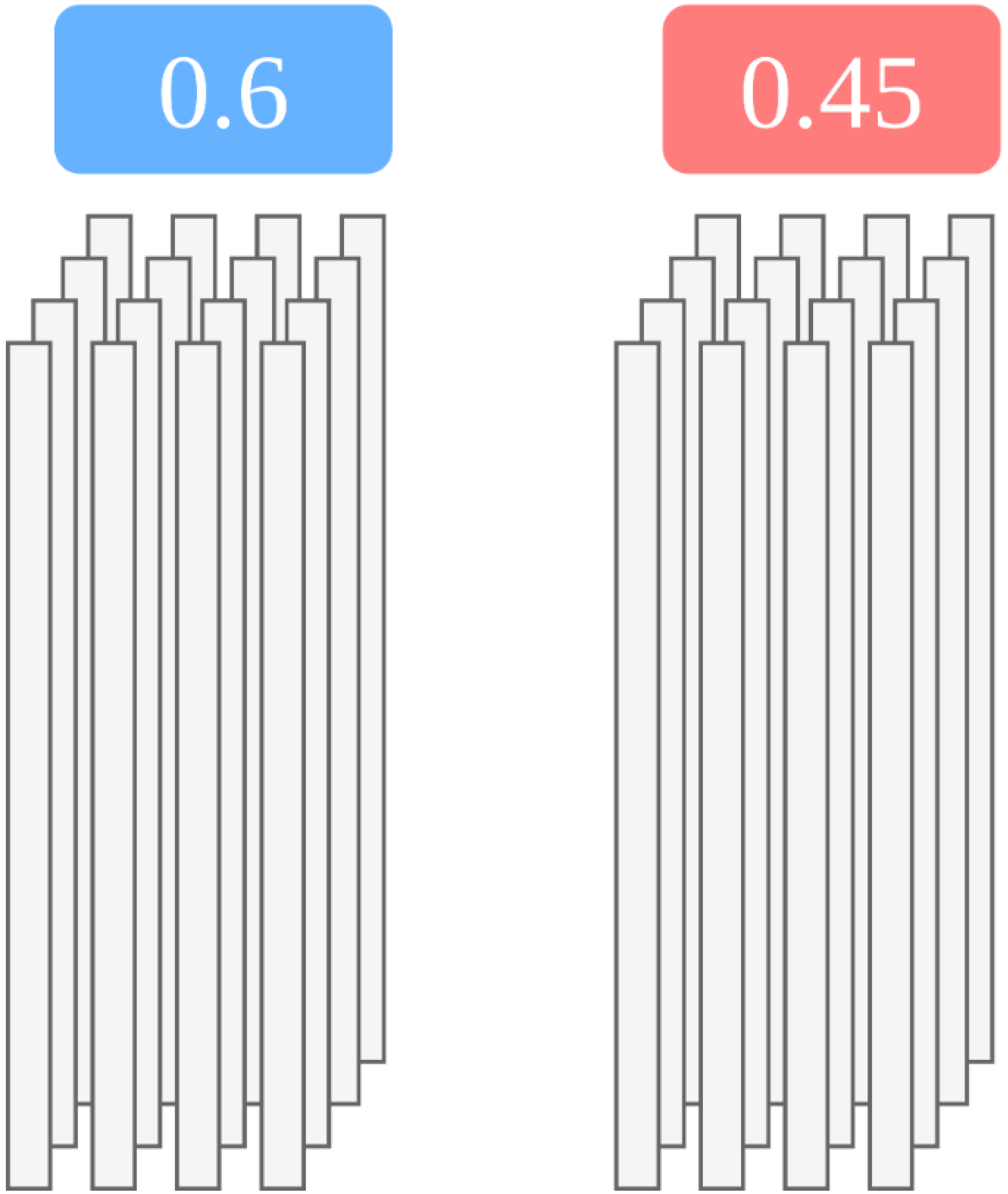

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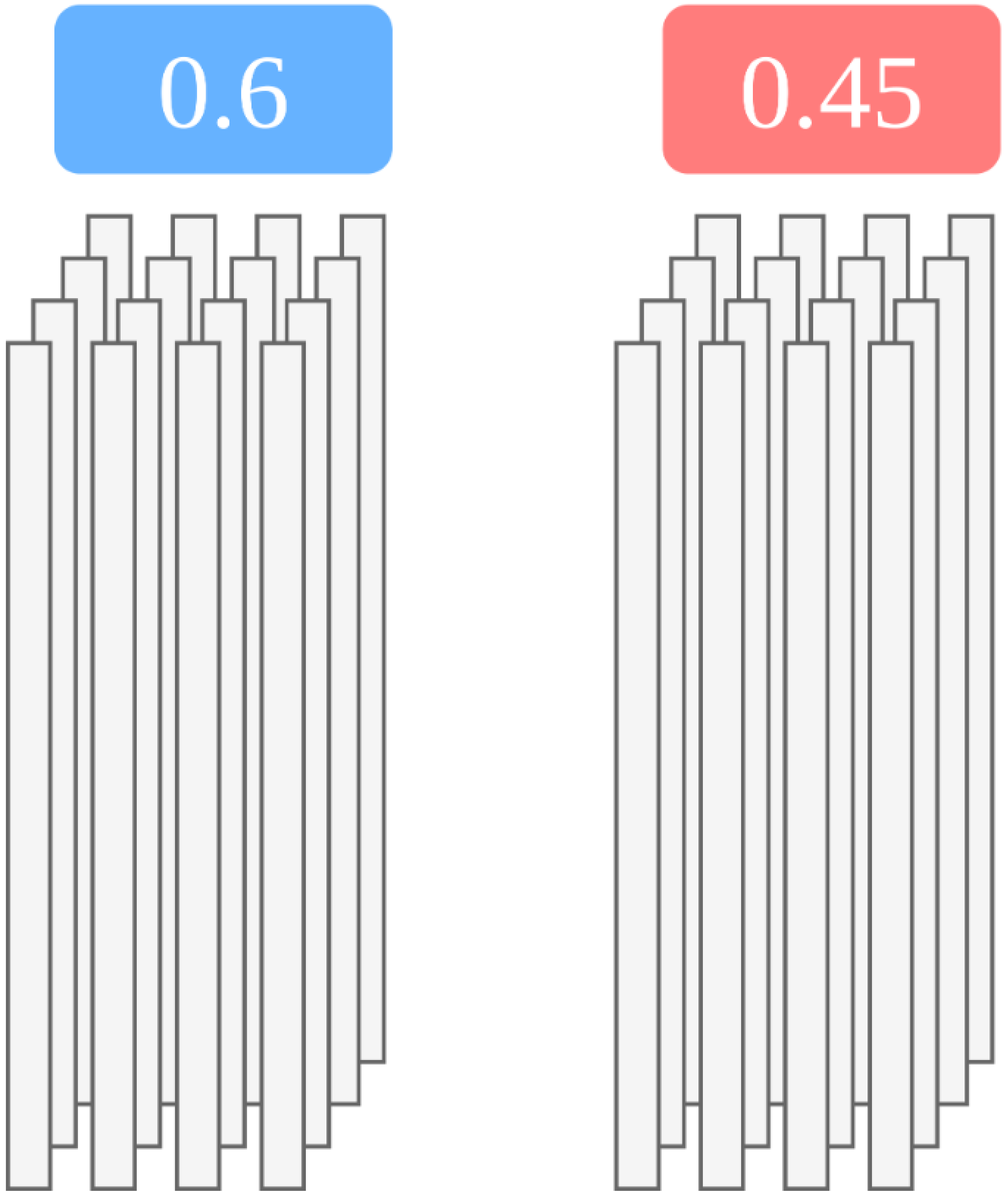

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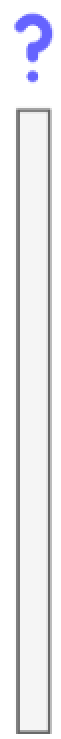
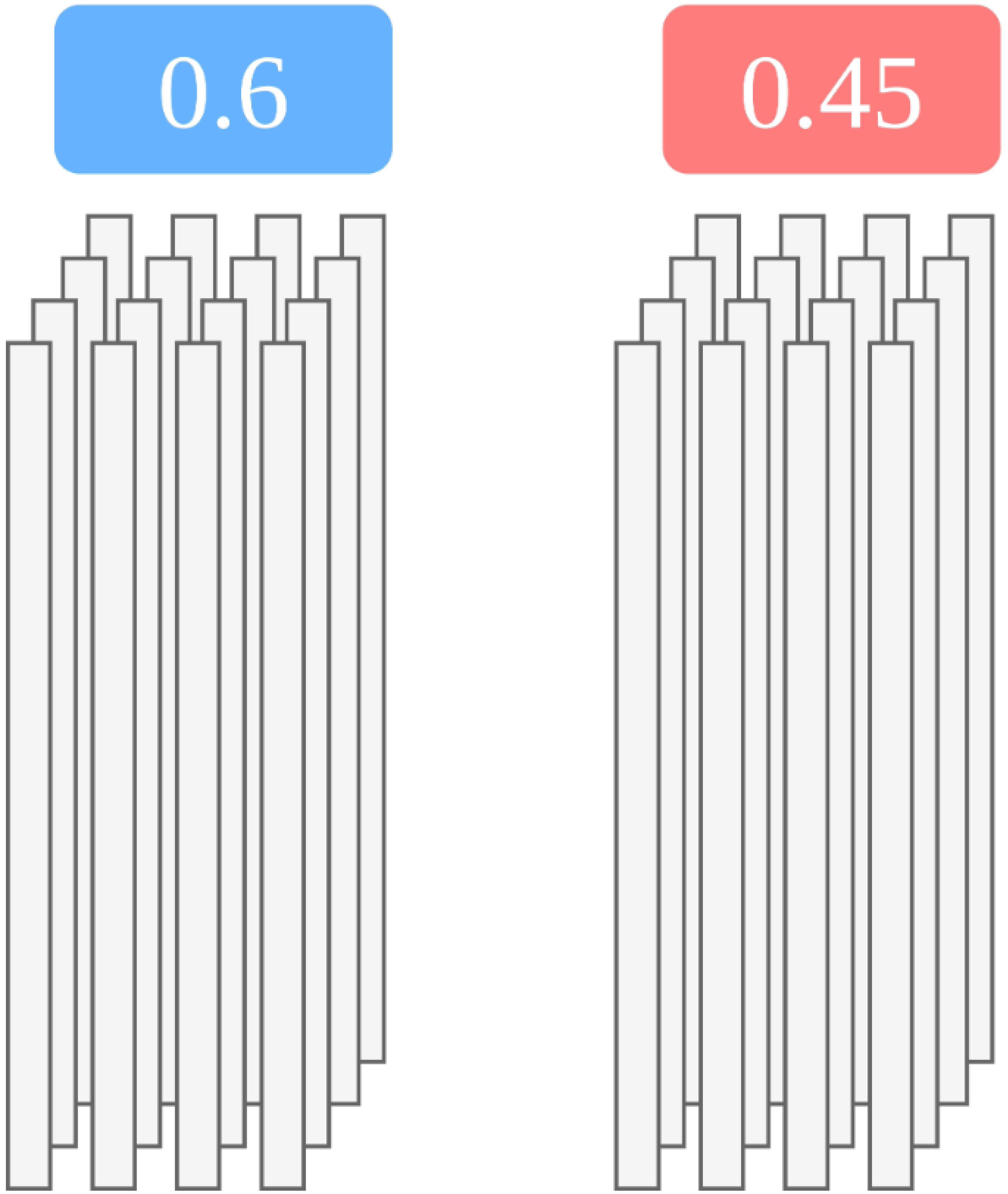
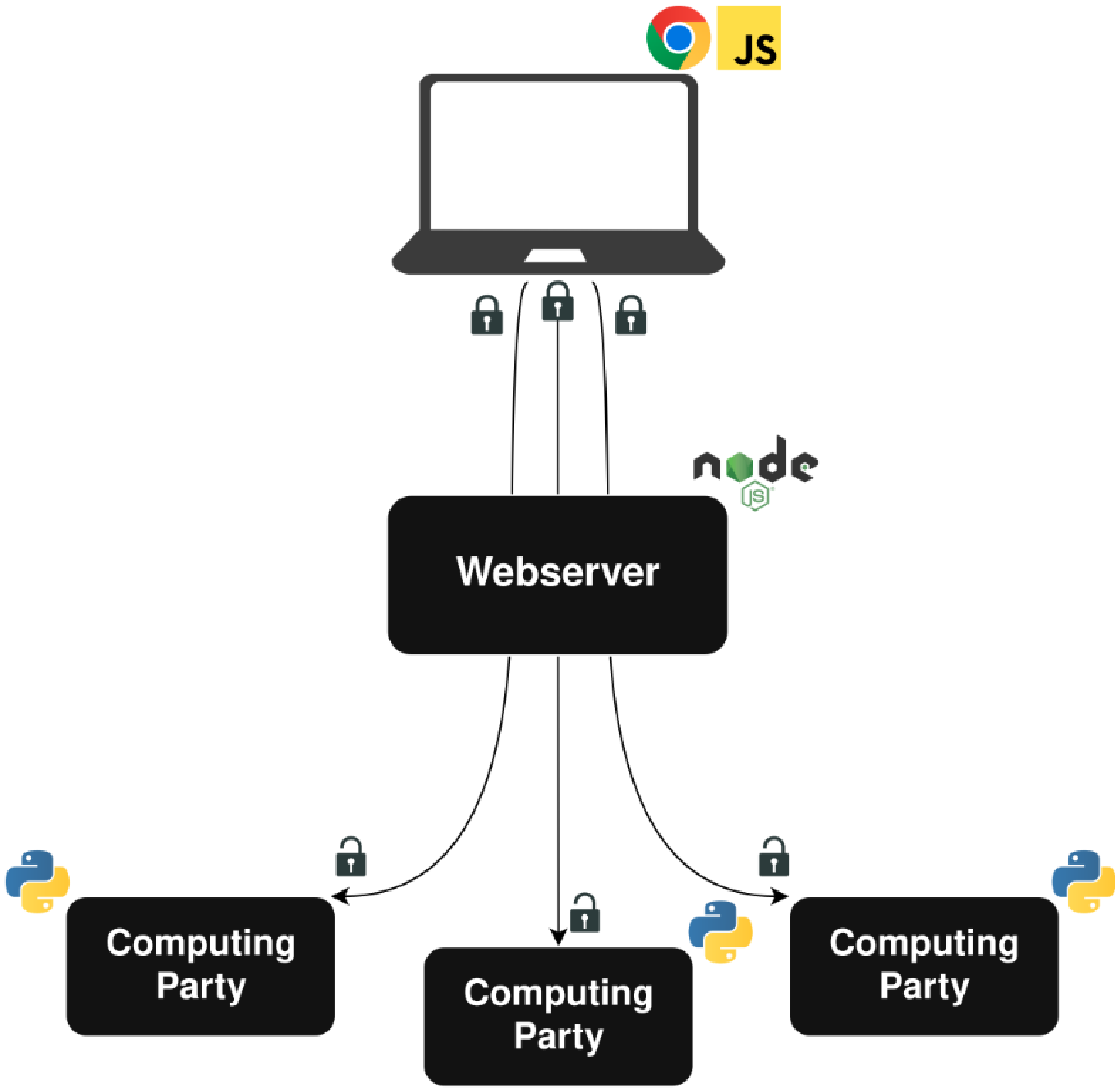


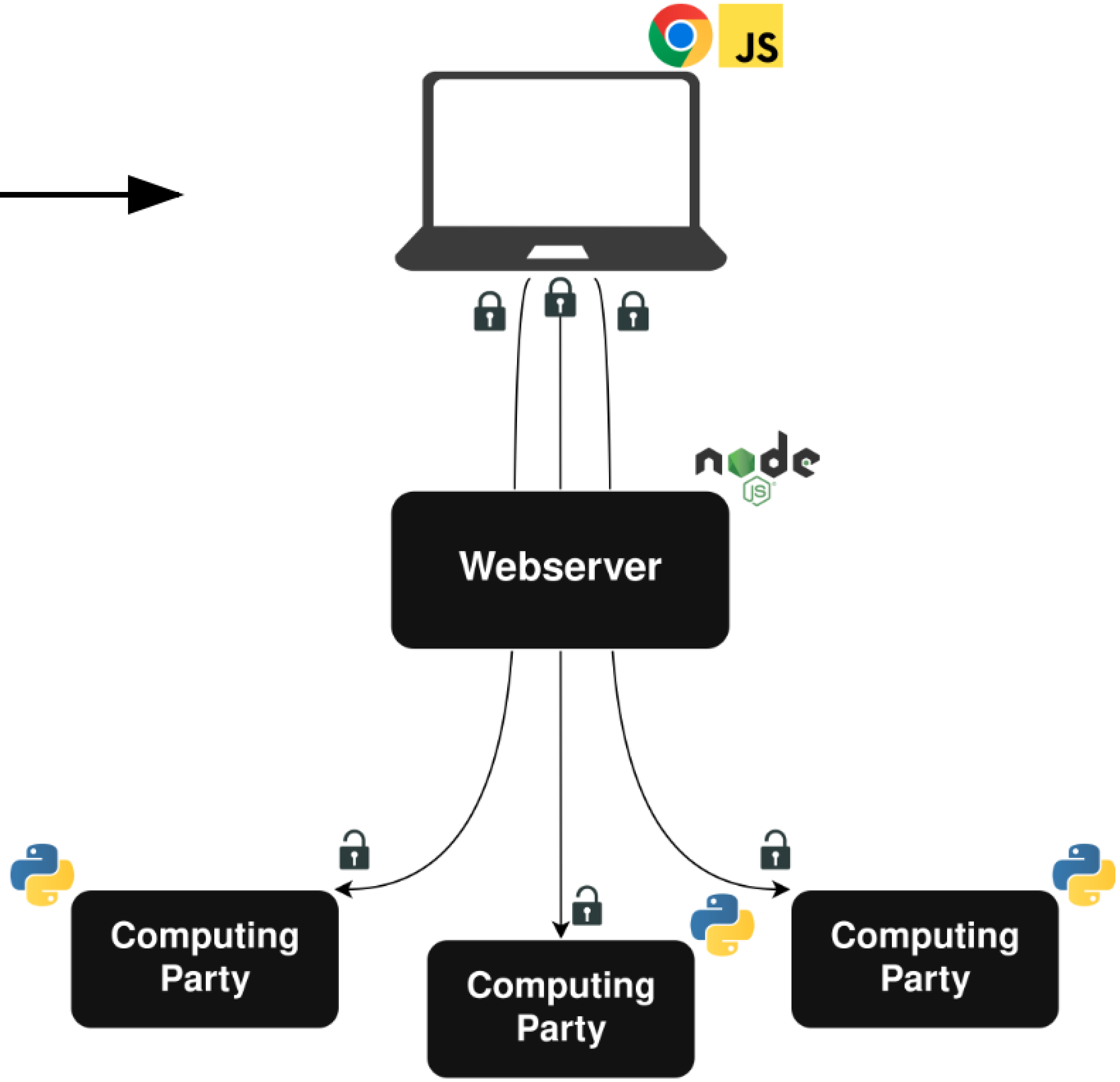


System Design



System Design

Client Plugin



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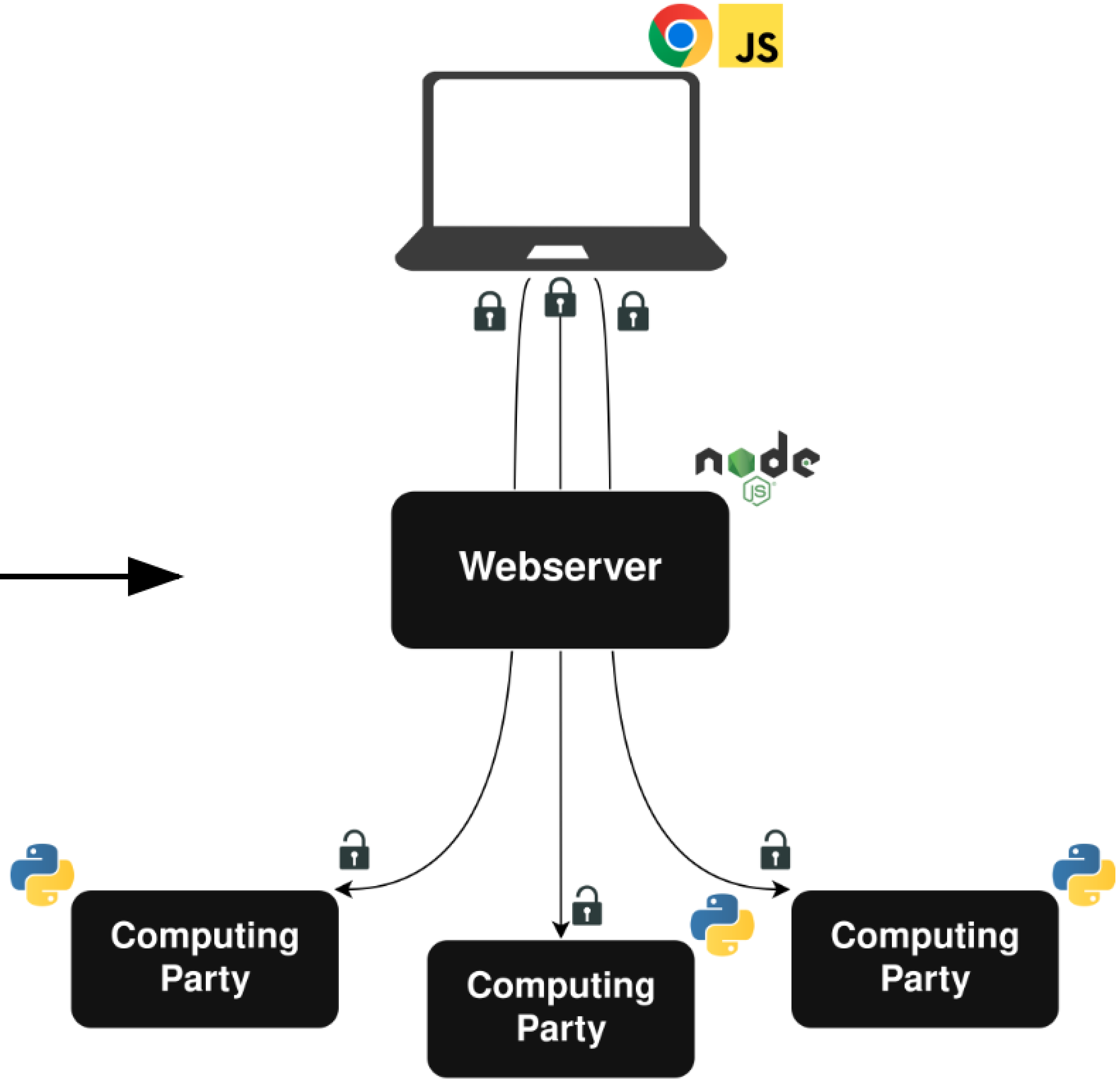

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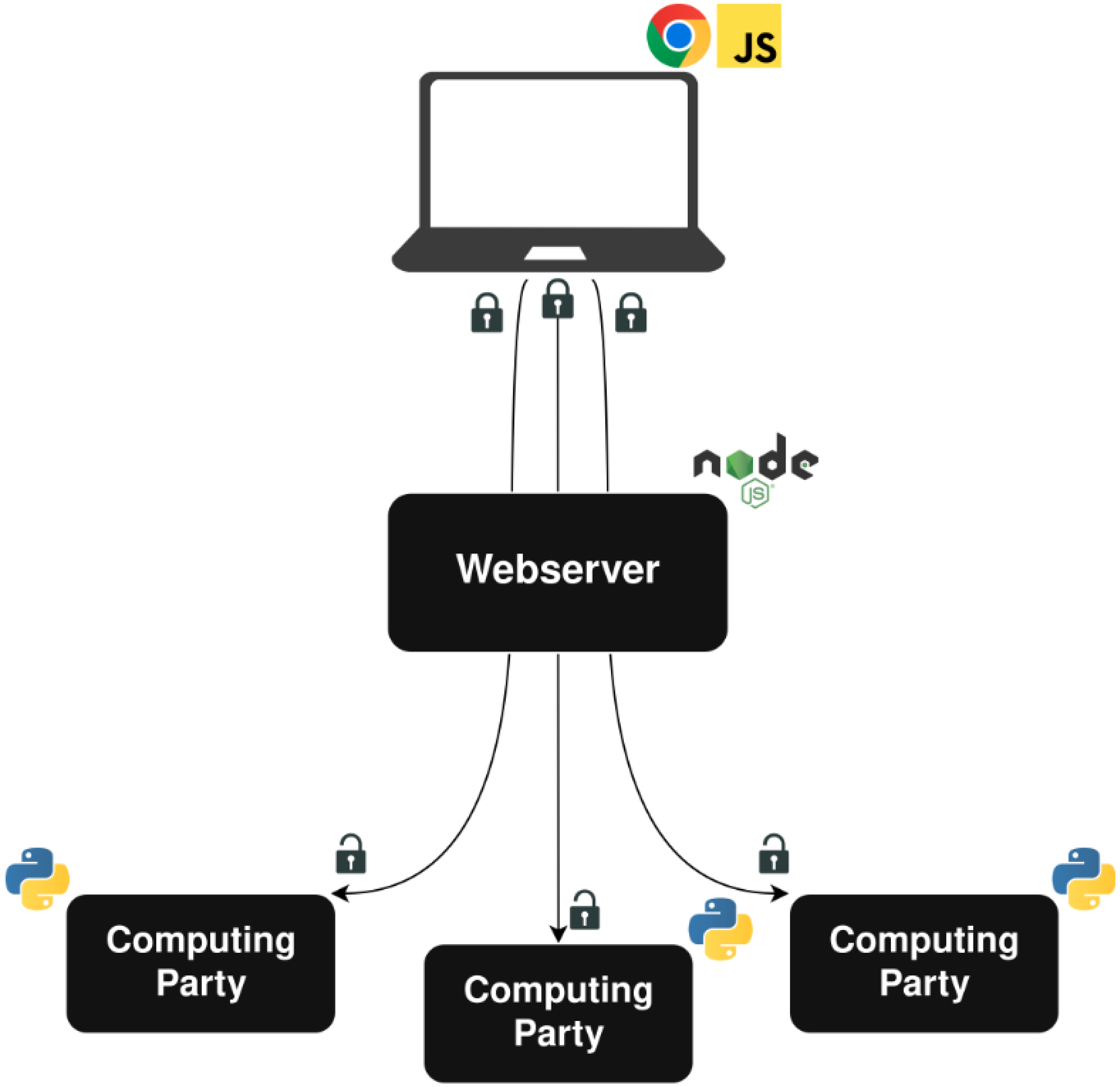
MPC Backend



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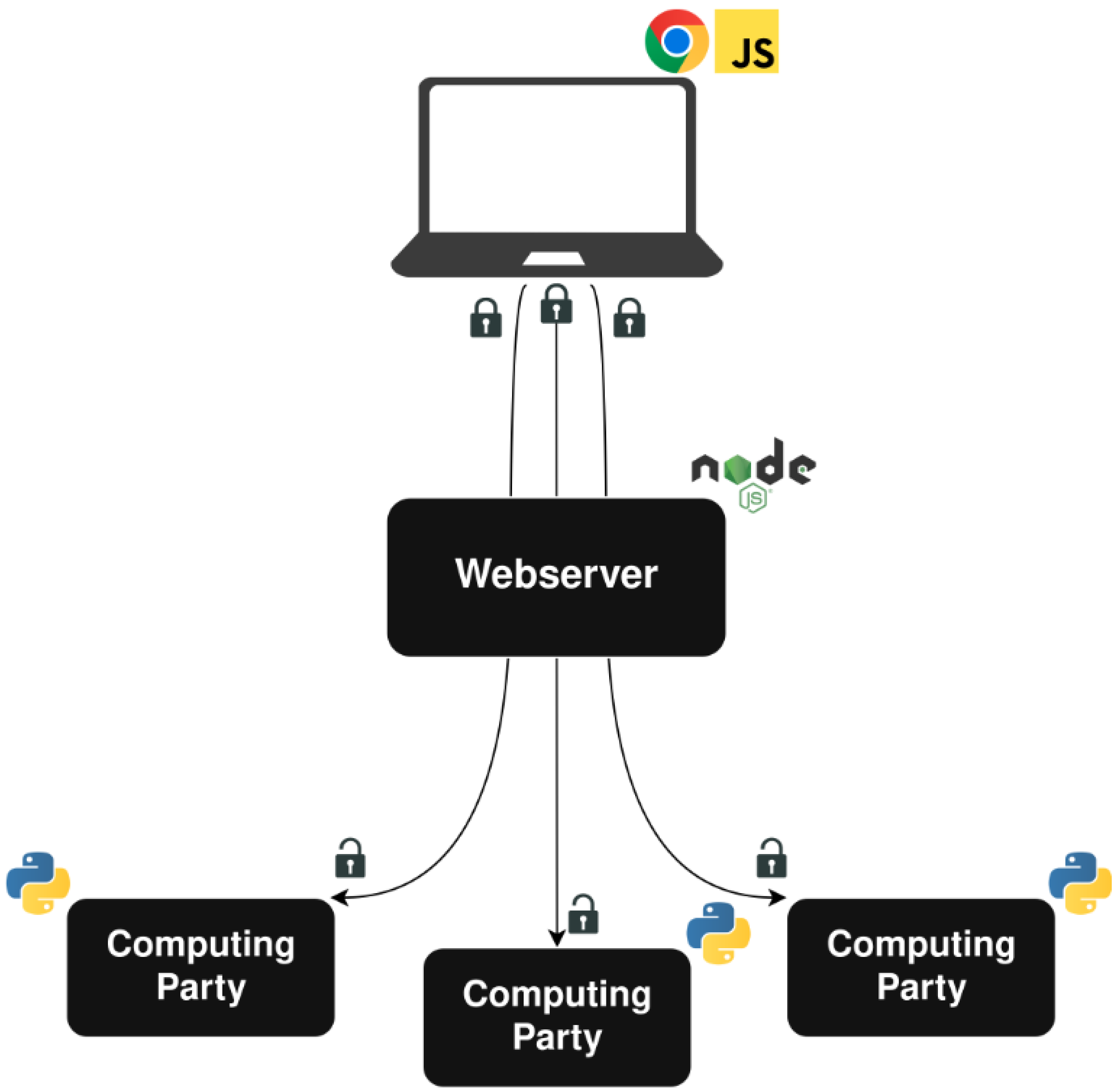

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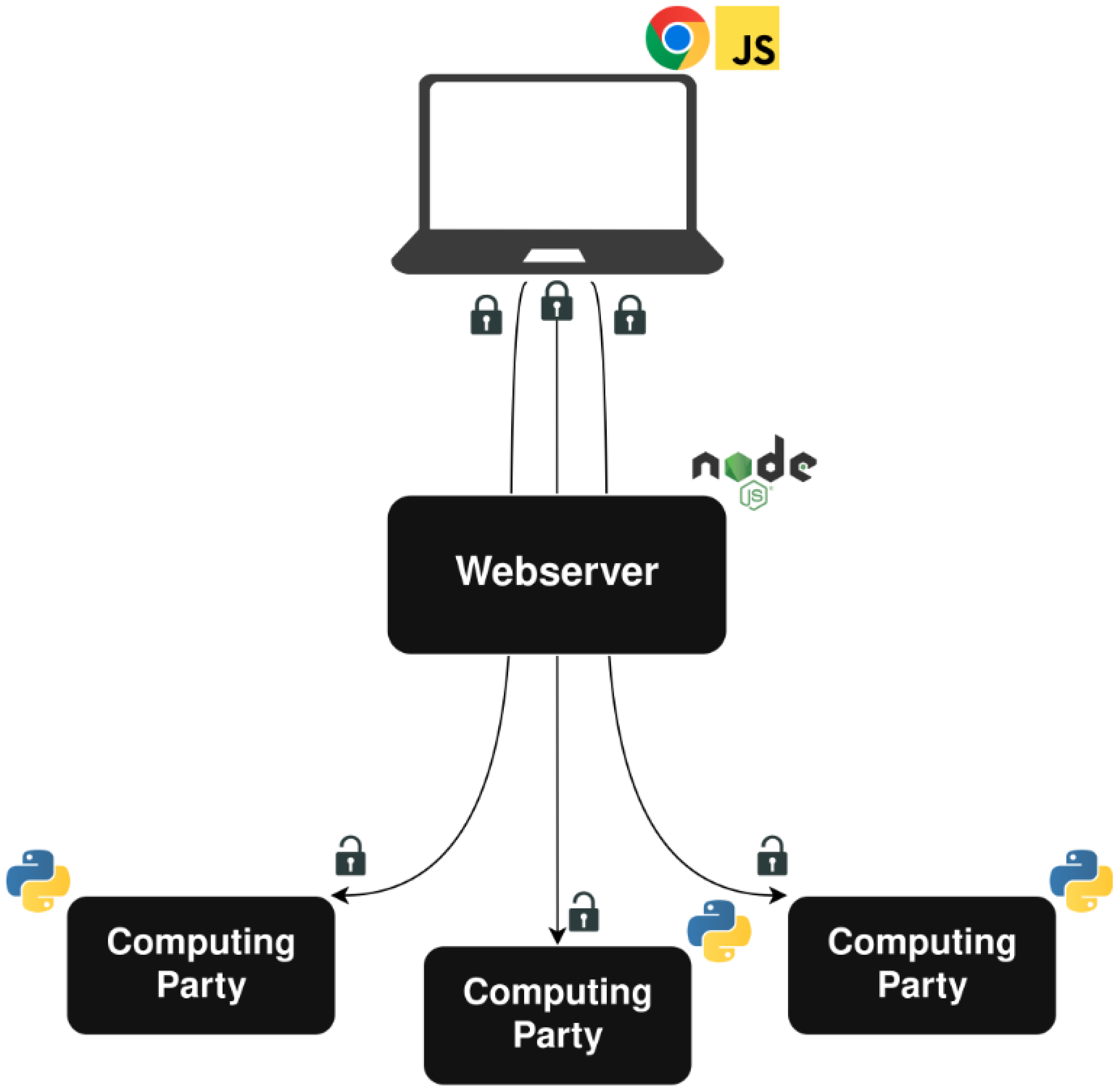

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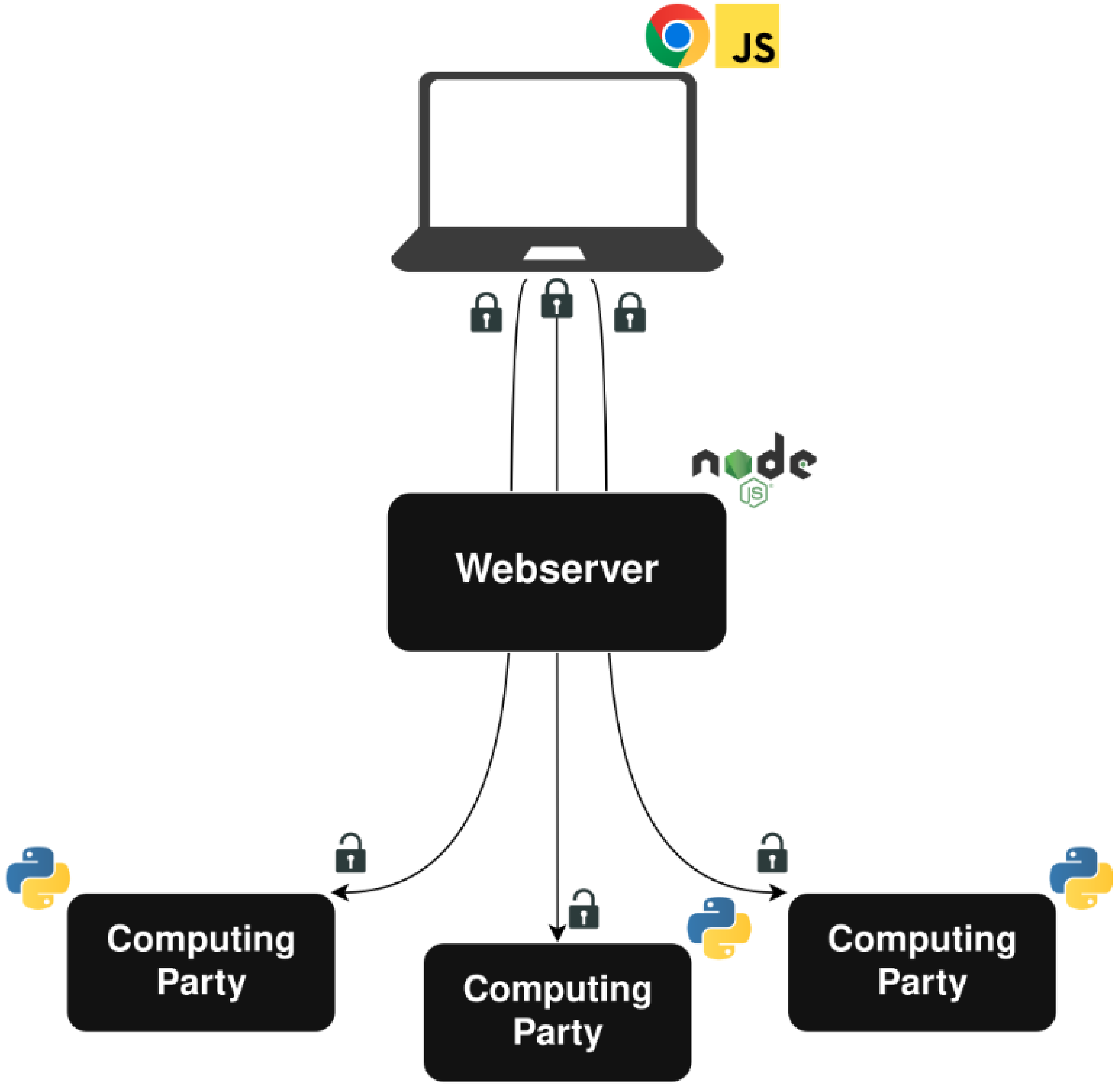

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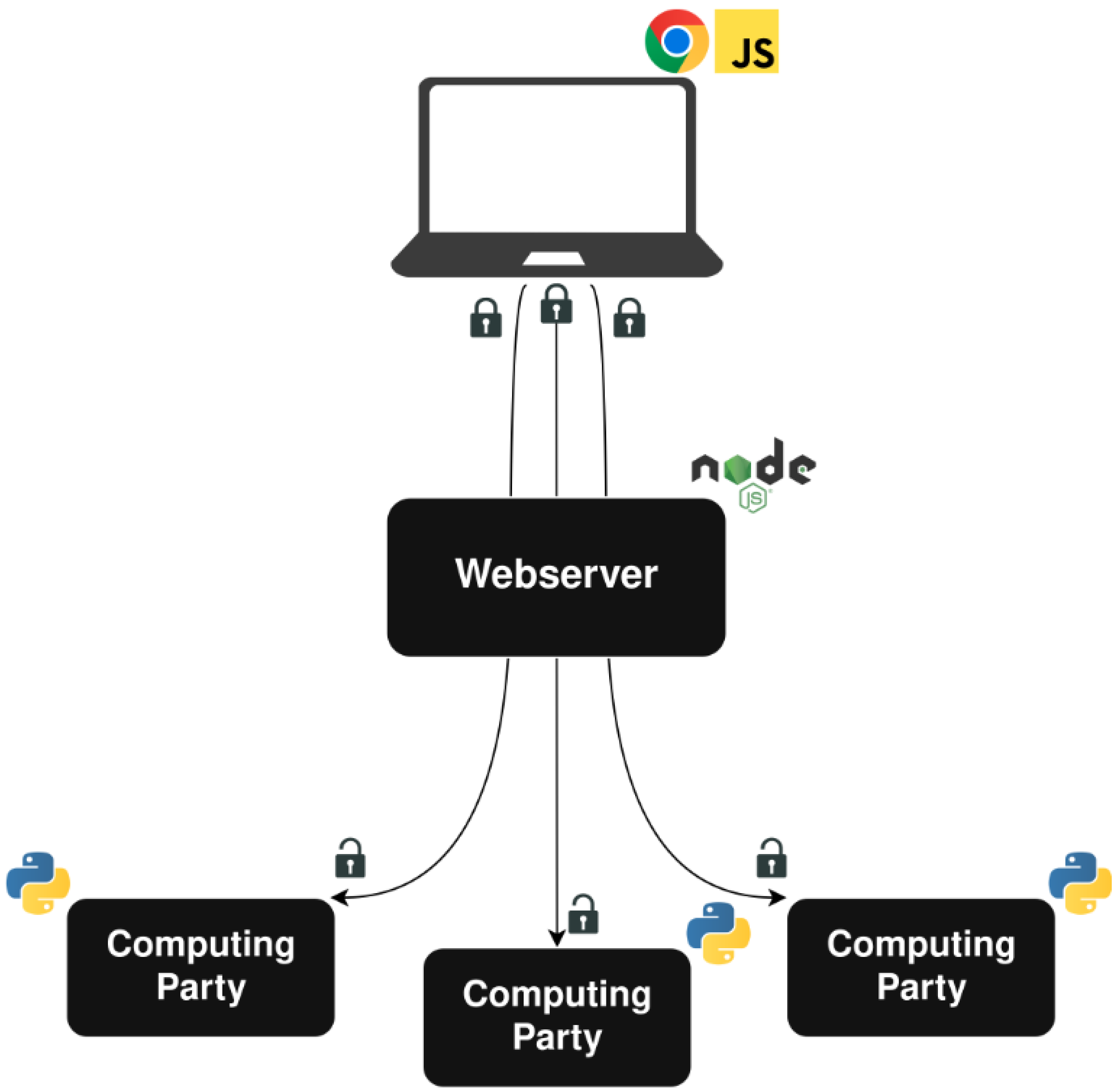

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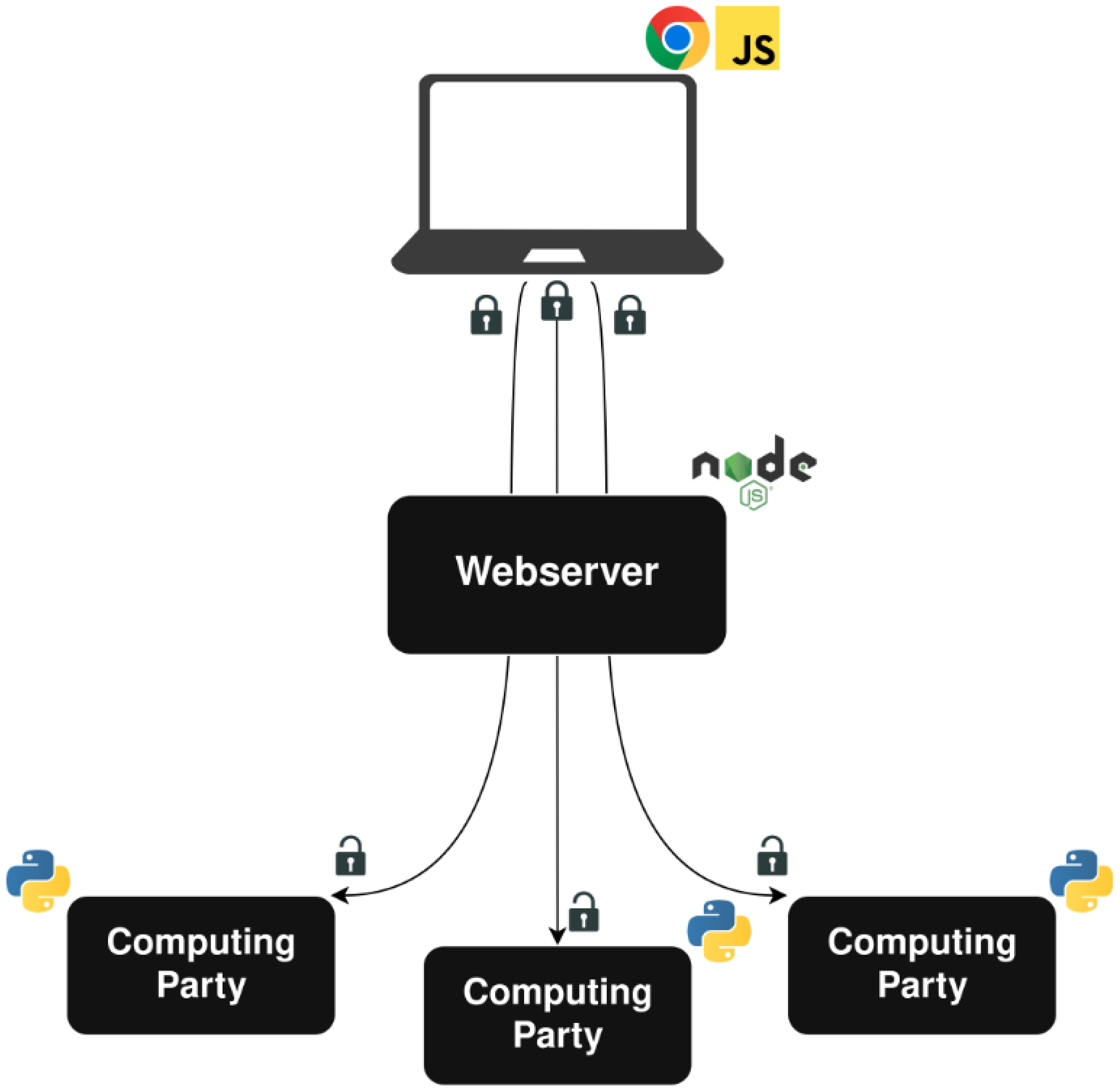

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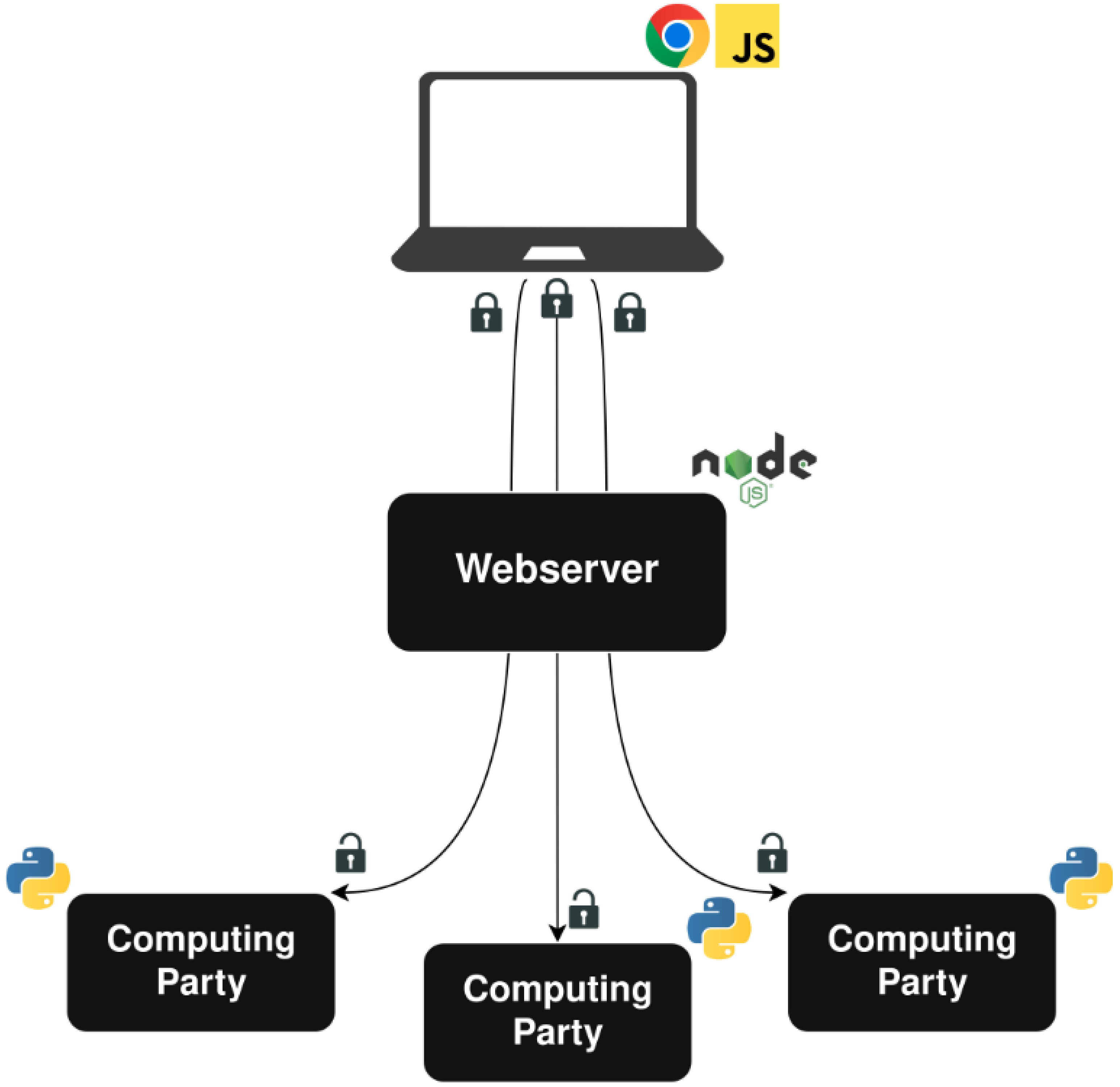

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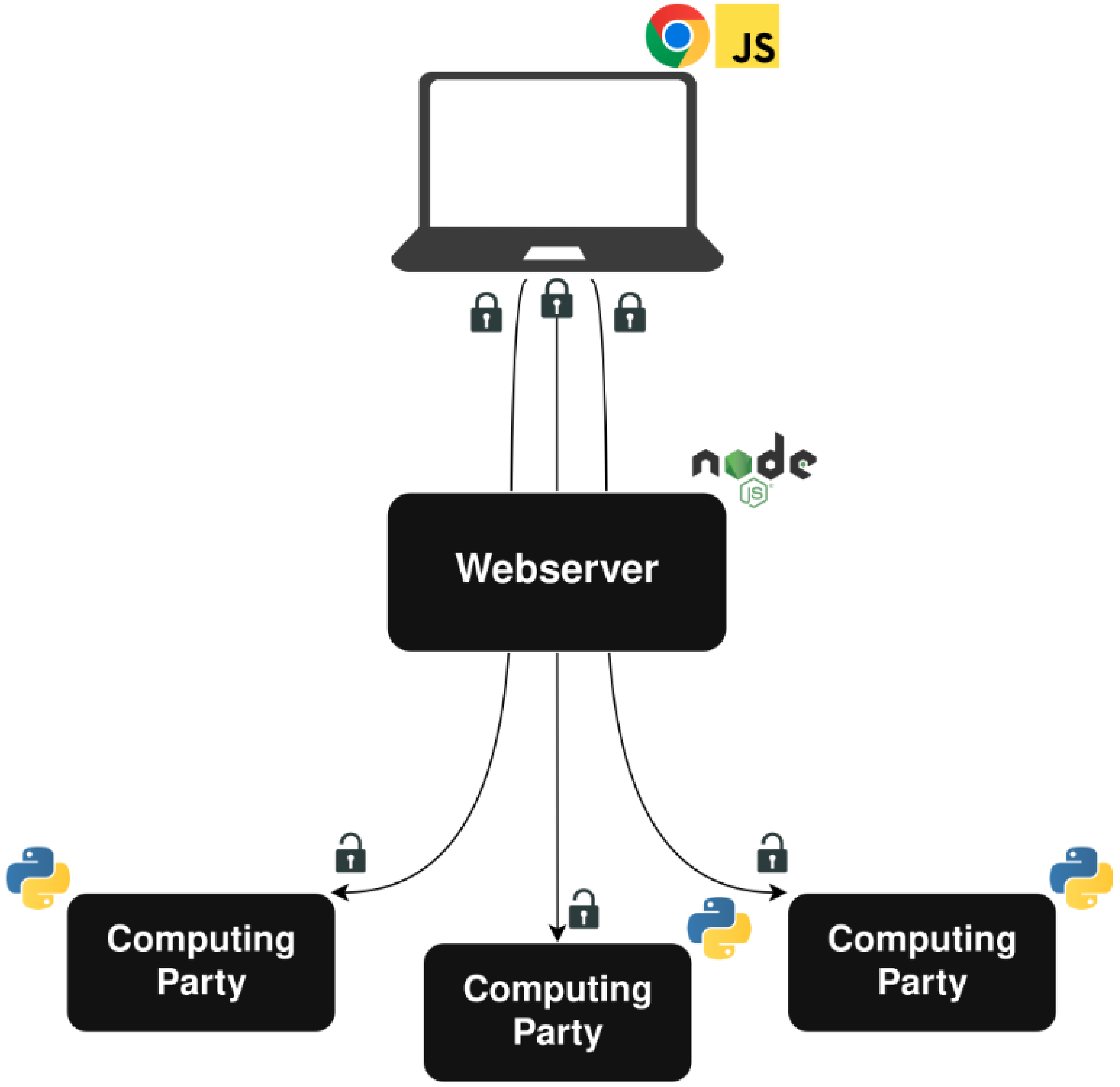
JS
node
Webserver
Computing Party
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Webserver

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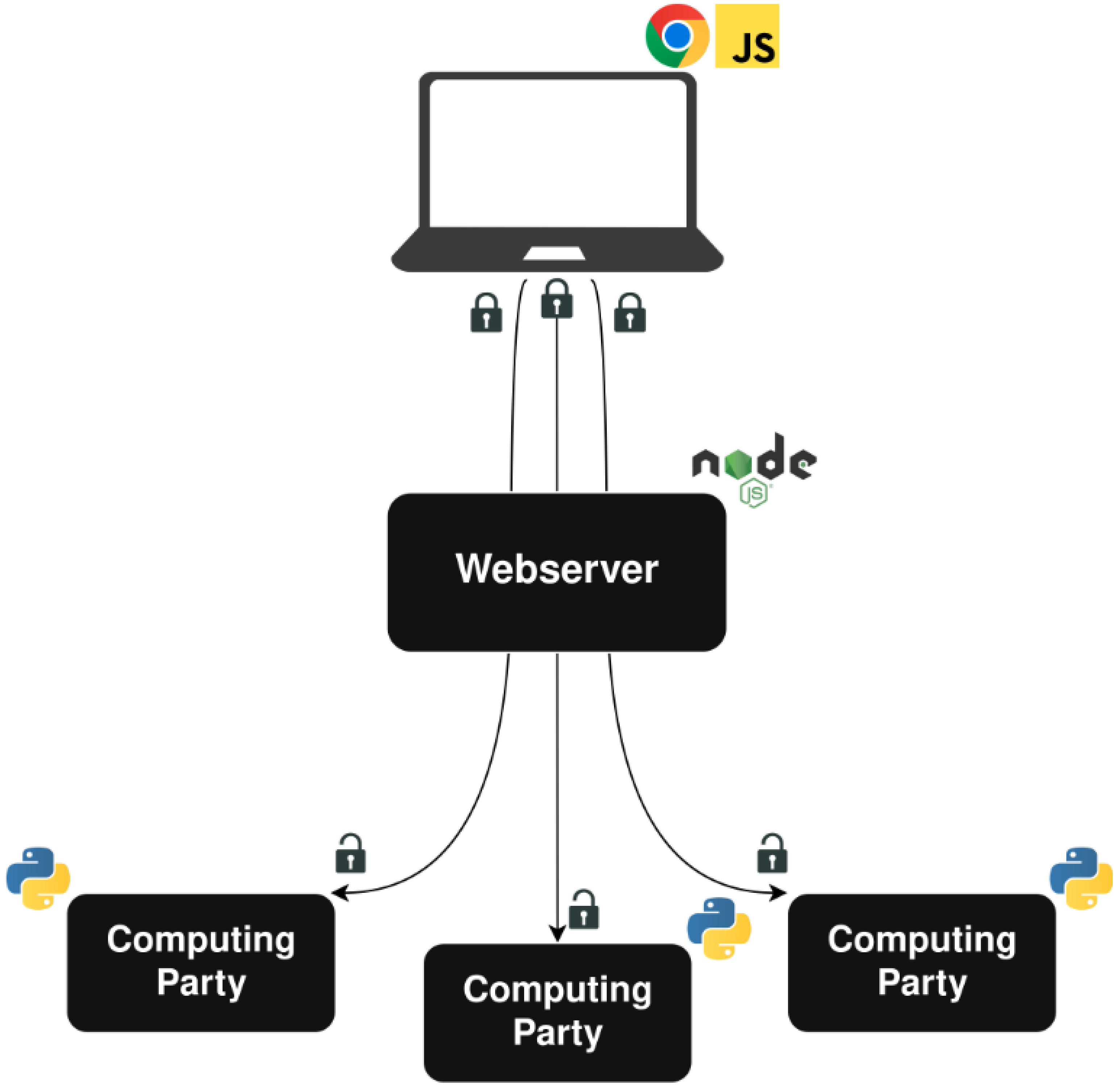

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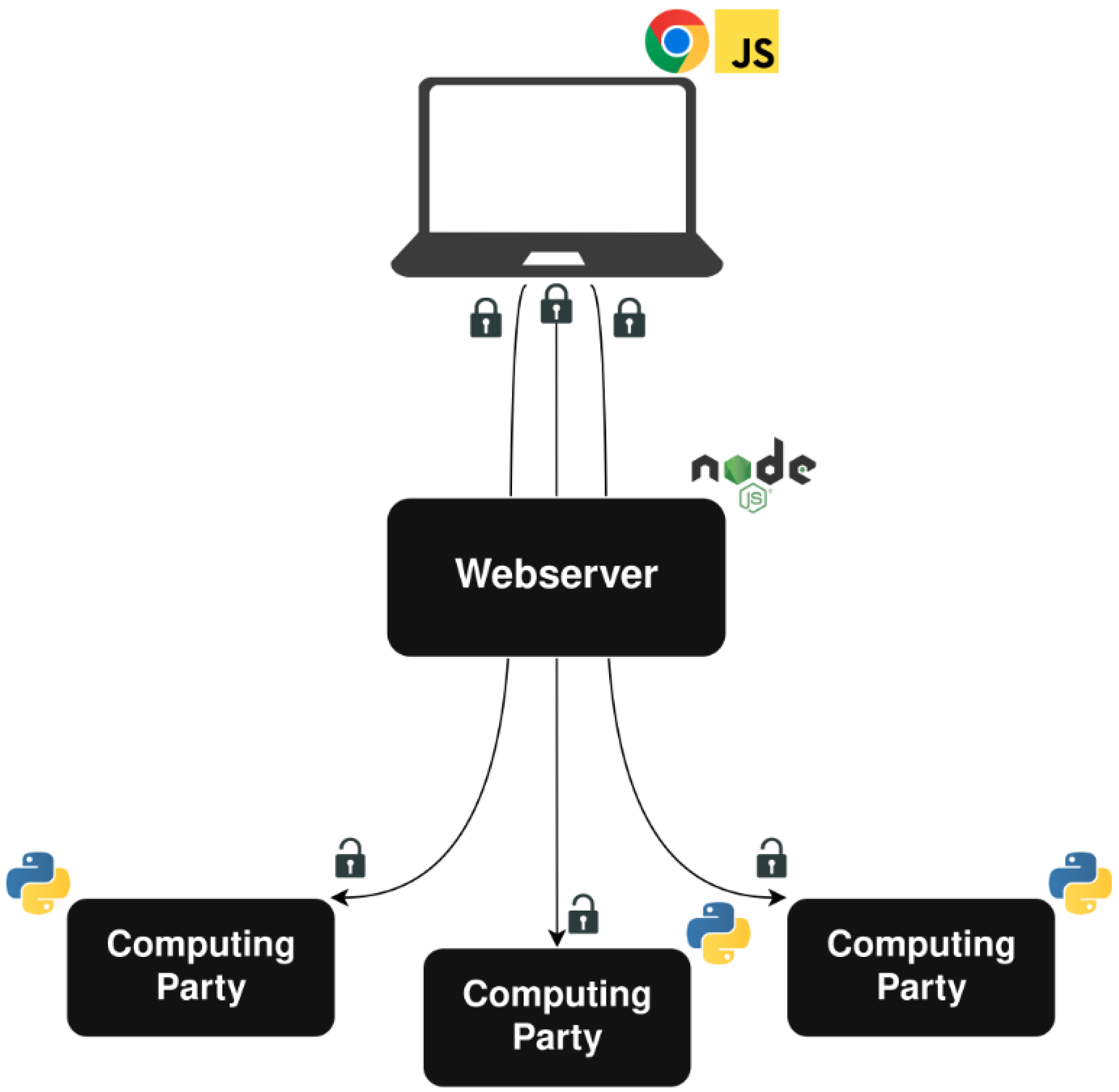
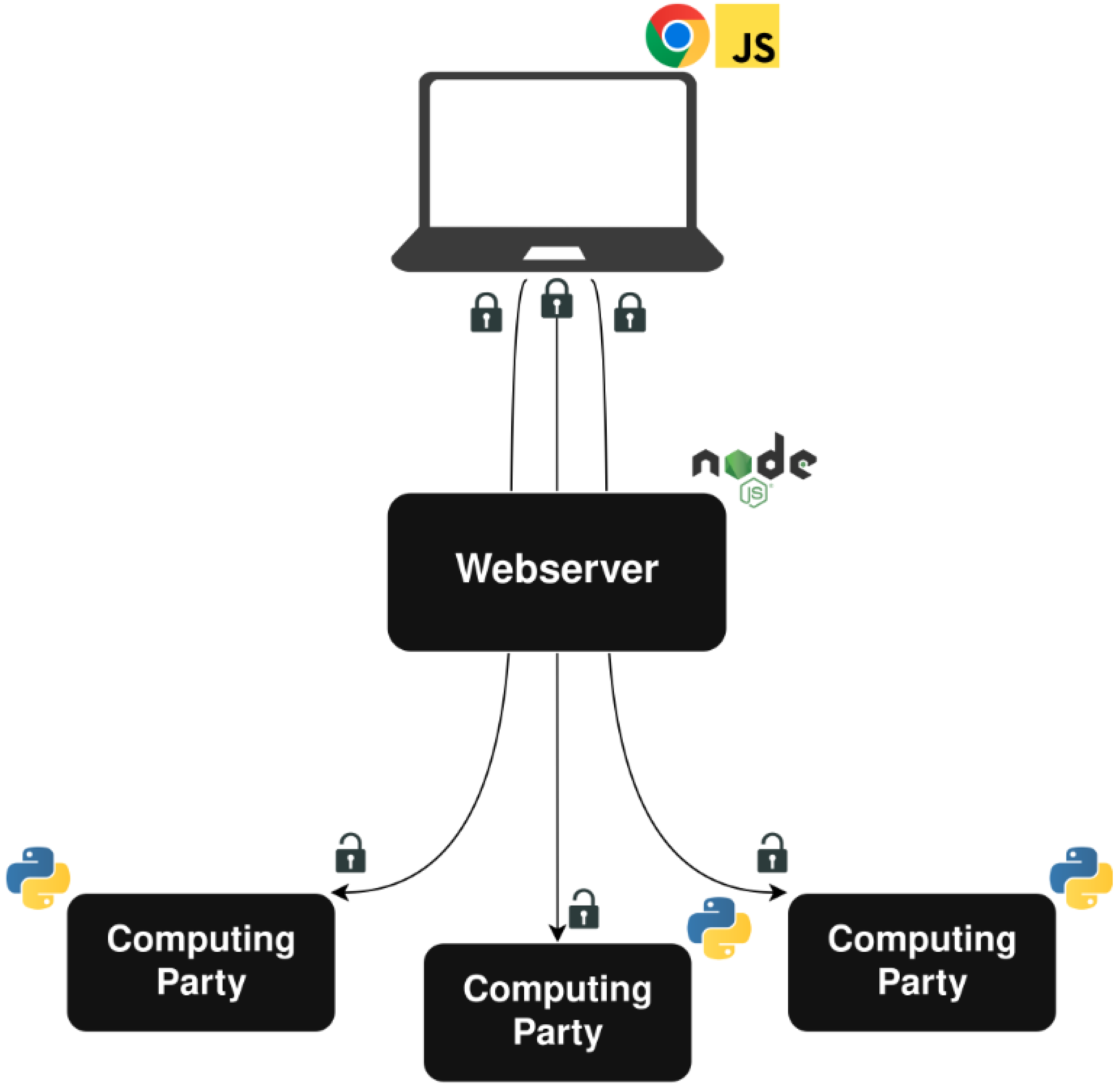


Webserver

- Simplifies interaction with clients
- Collects basic metadata
- Never sees any private data



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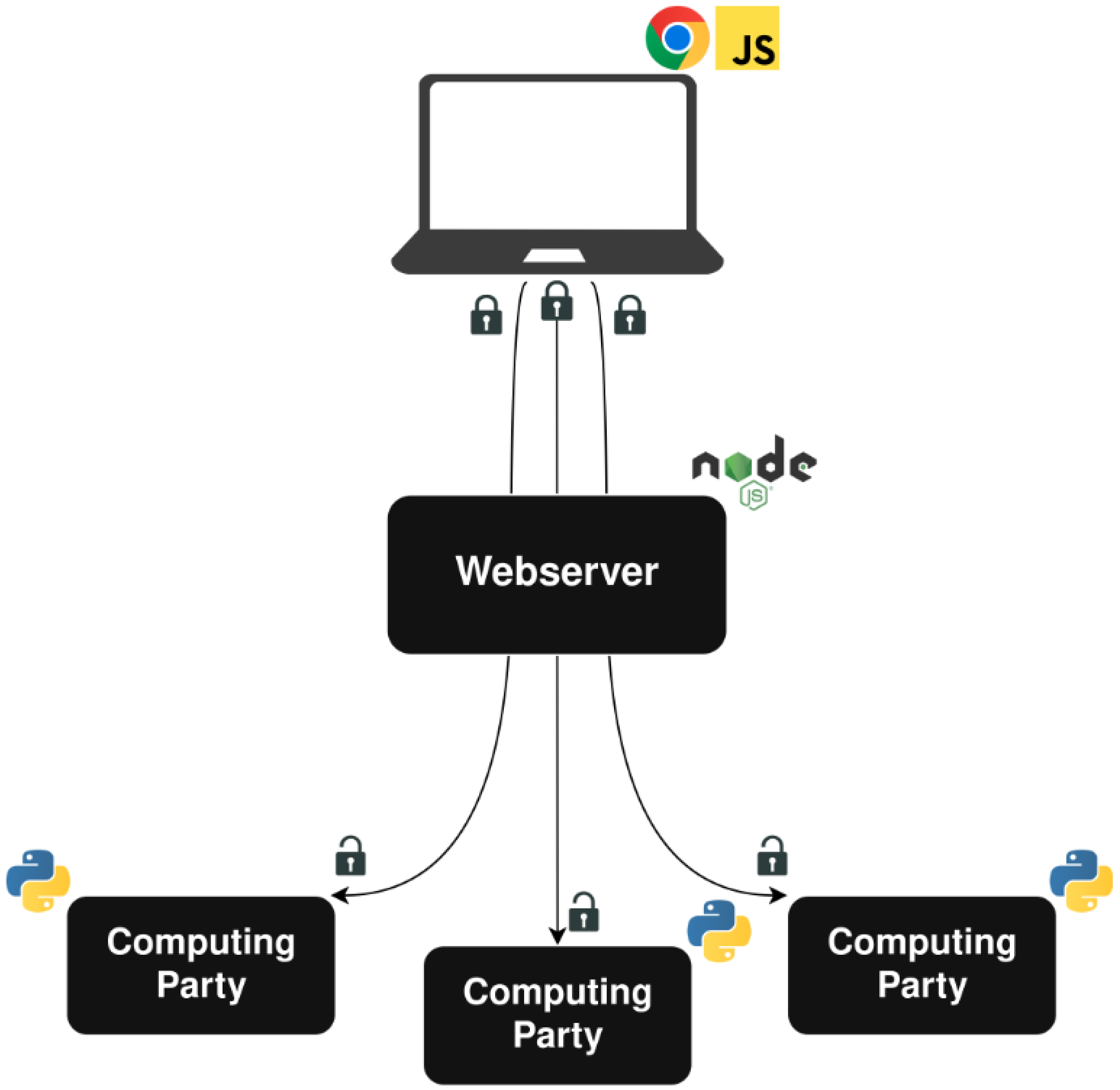
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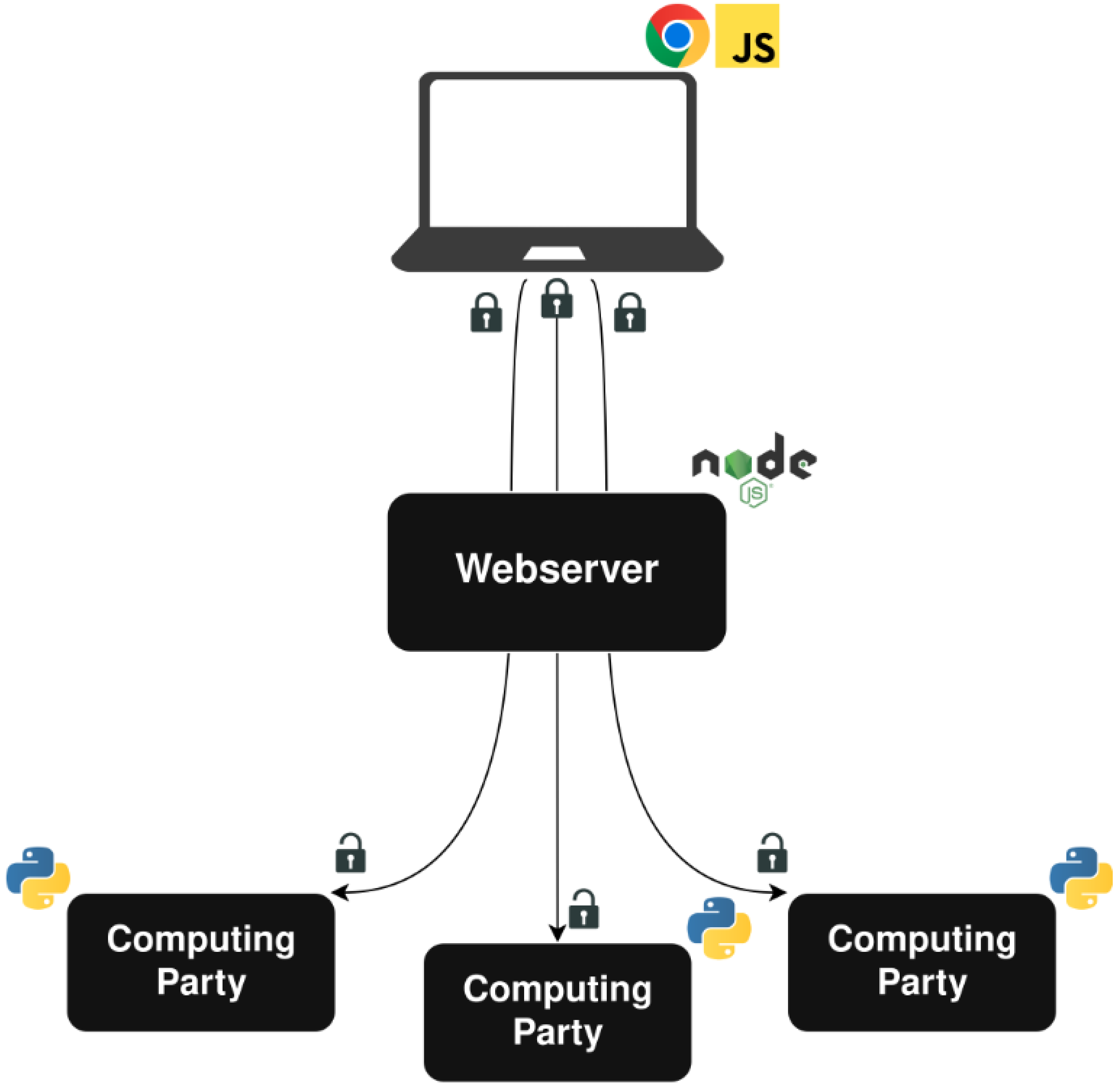

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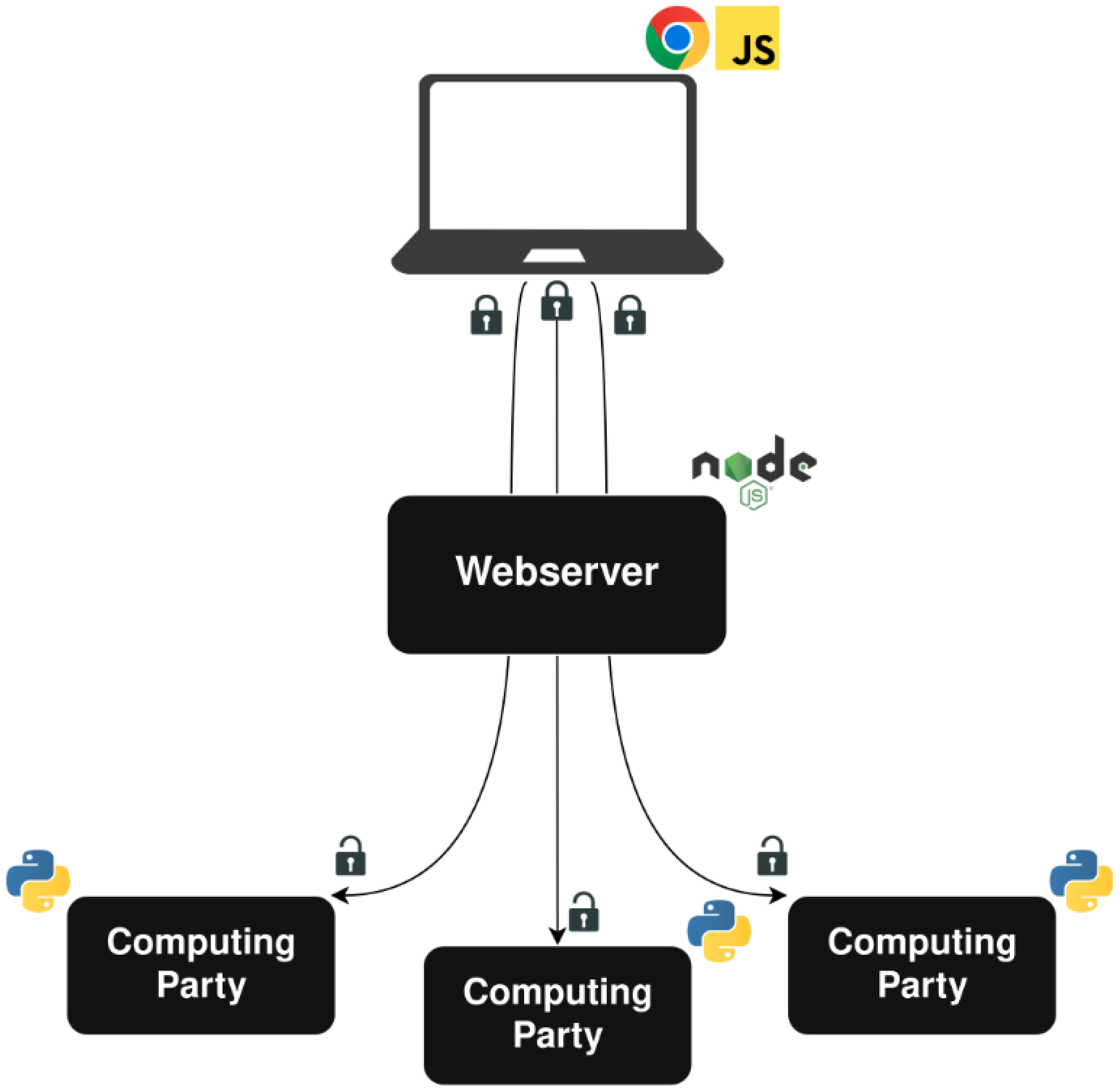

MPC Backend

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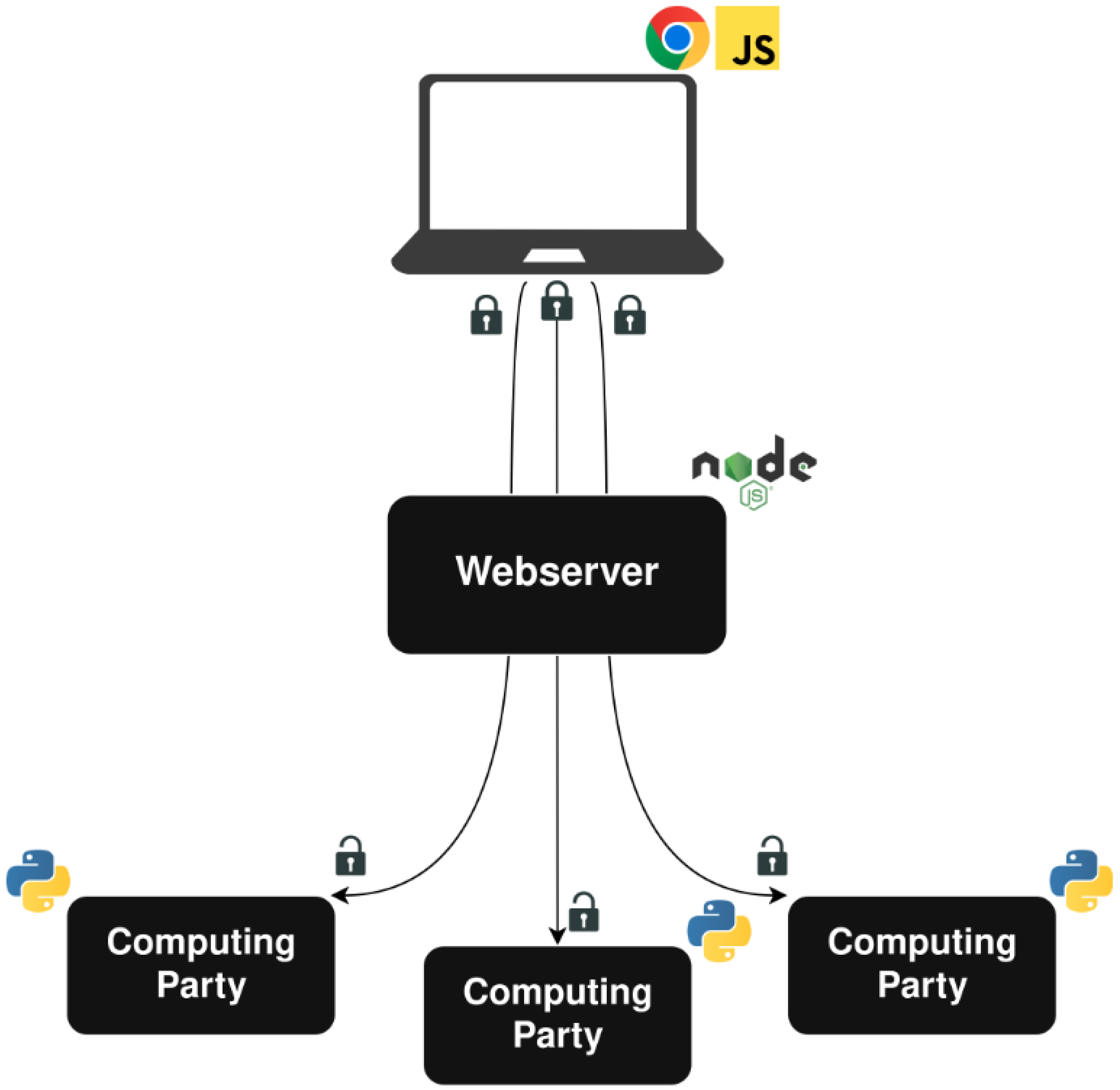
- Three party computation with an honest majority



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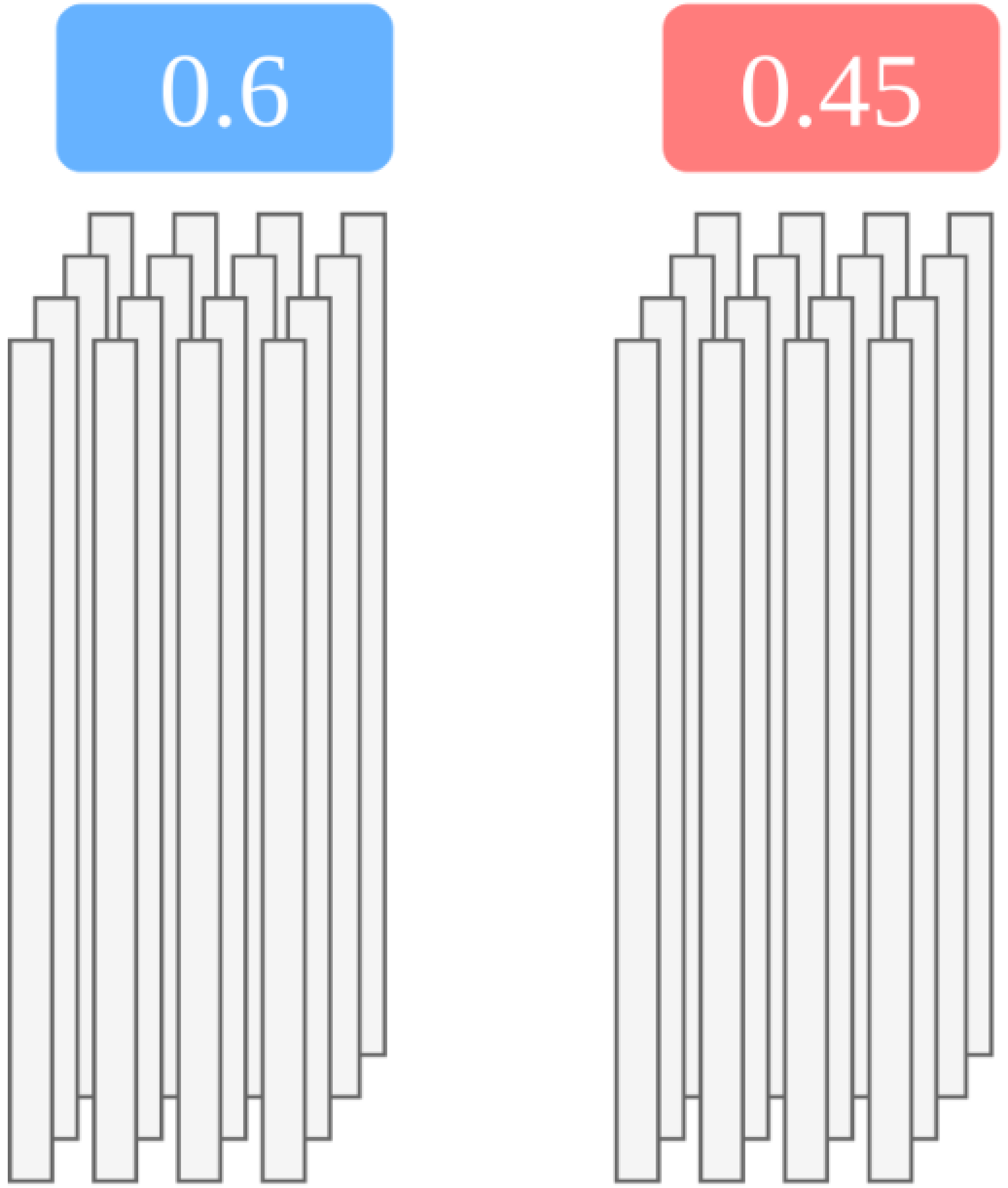

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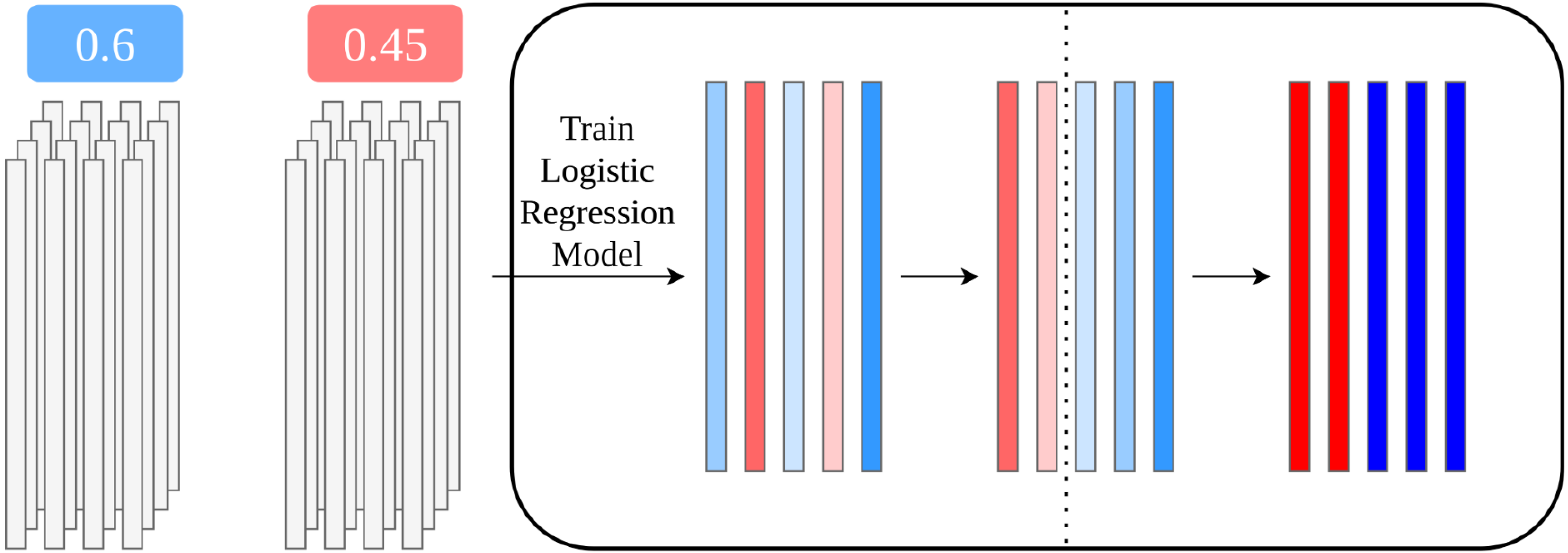

Repeat Until Convergence

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- Updated label assignment and convergence checking use secure comparisons
- Practically efficient
- Code will be open source in the future

Lessons Learned and Future Directions

Data Integrity Matters

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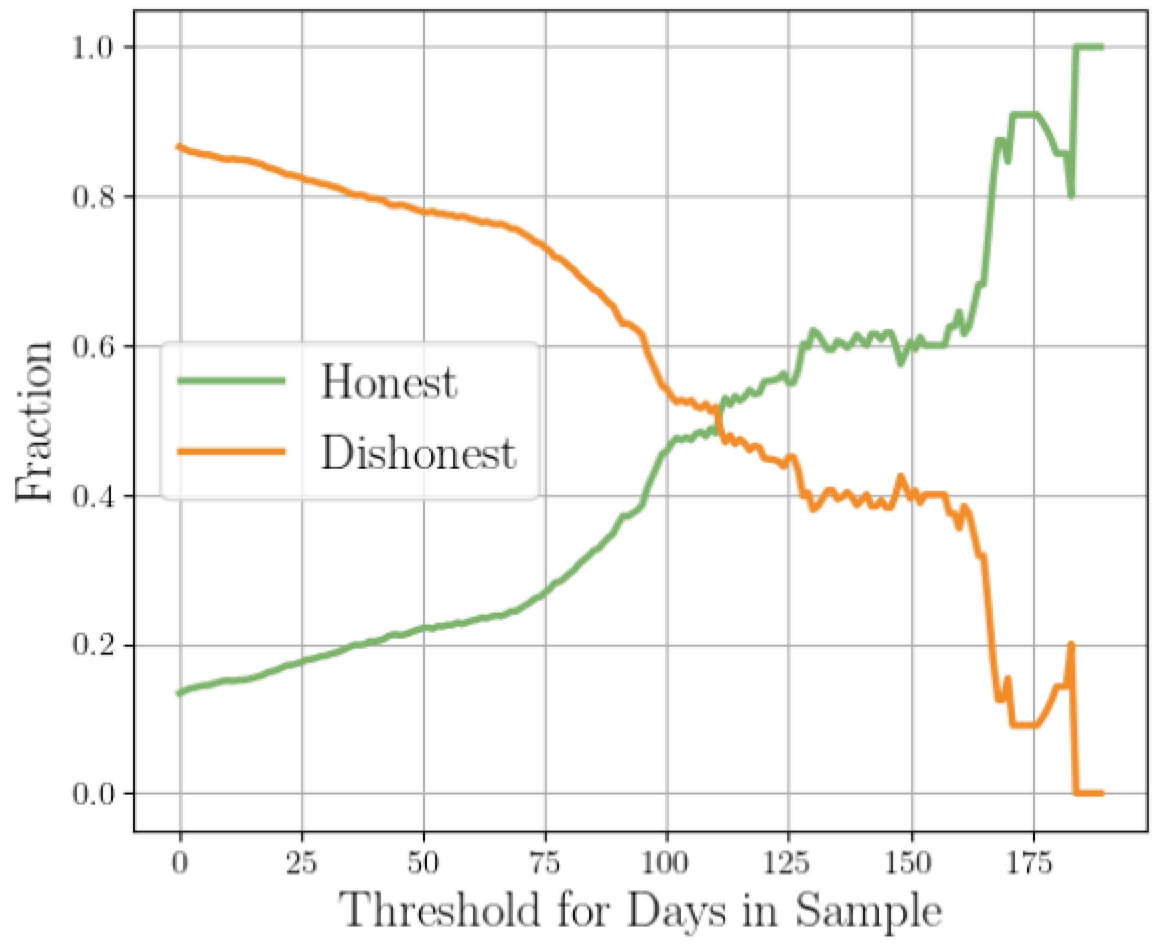

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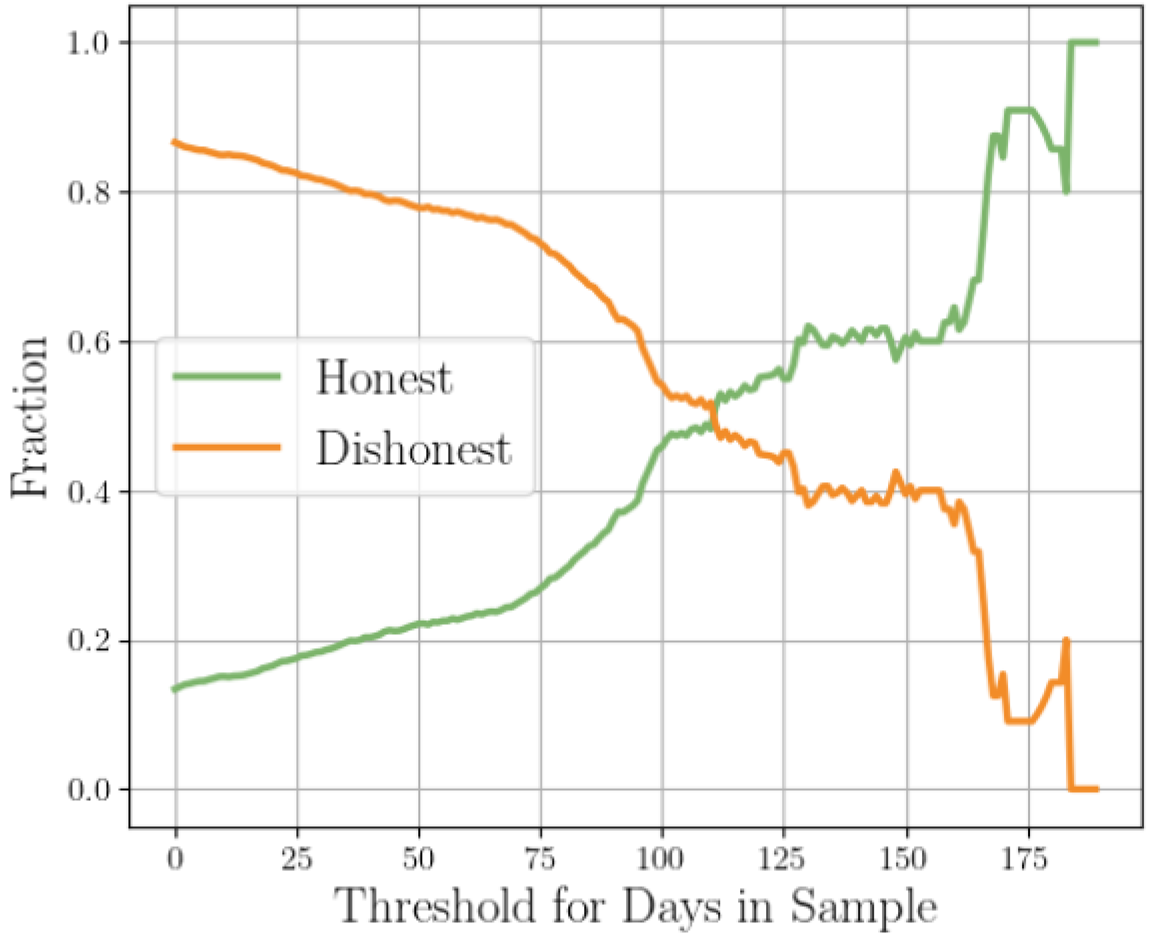

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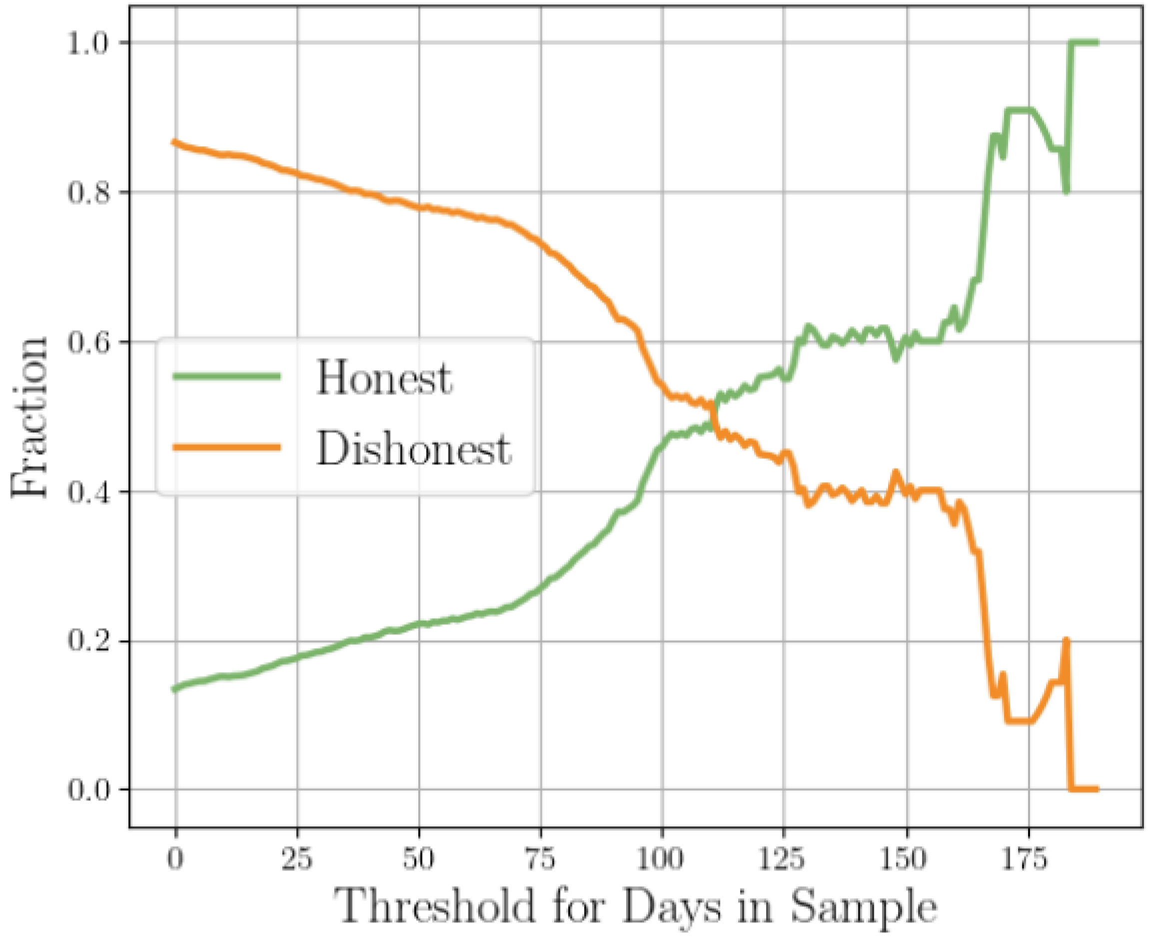

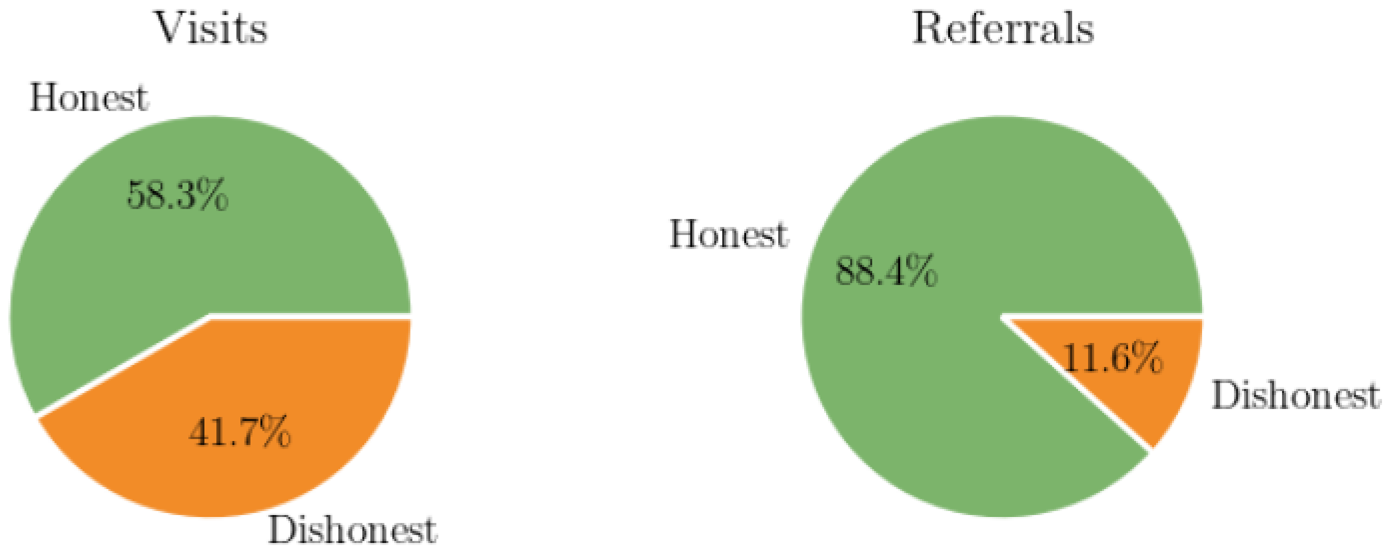

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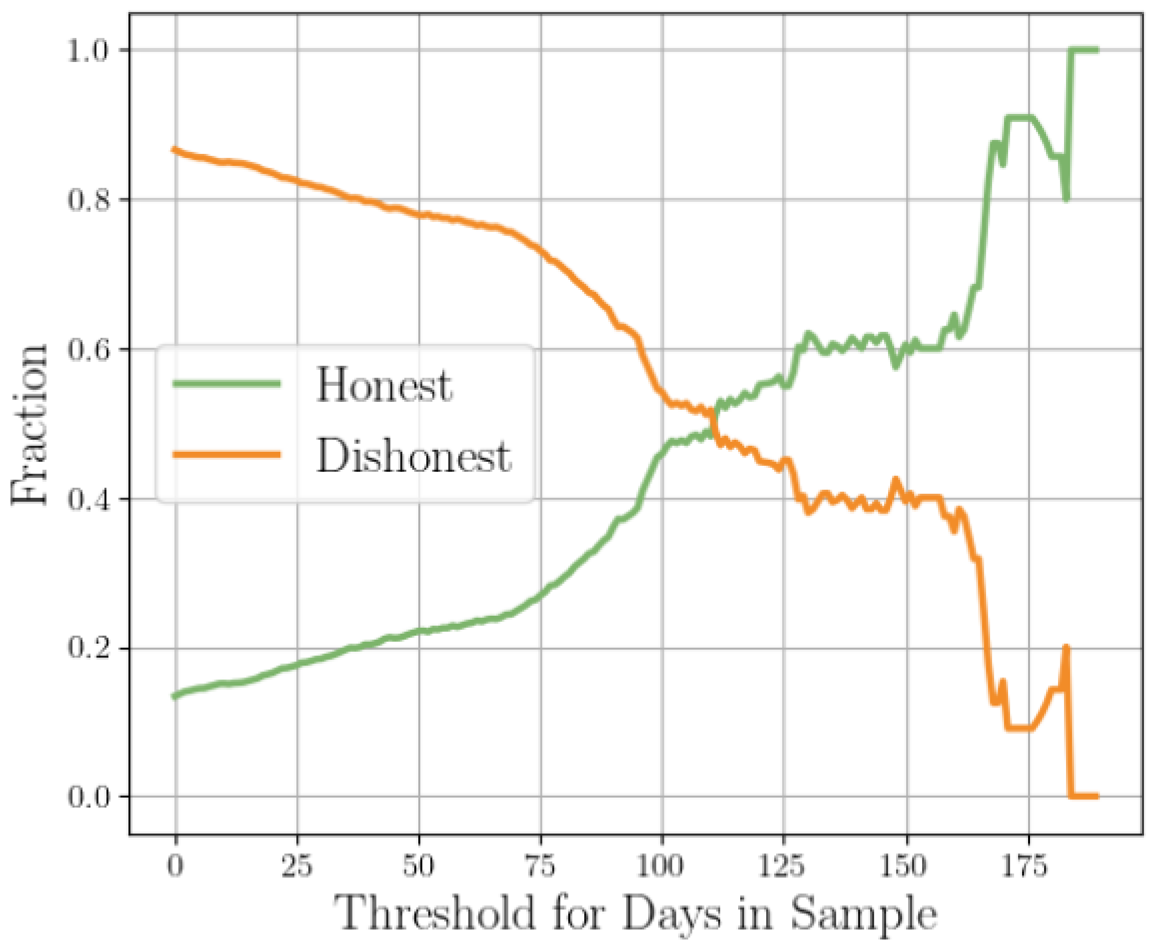
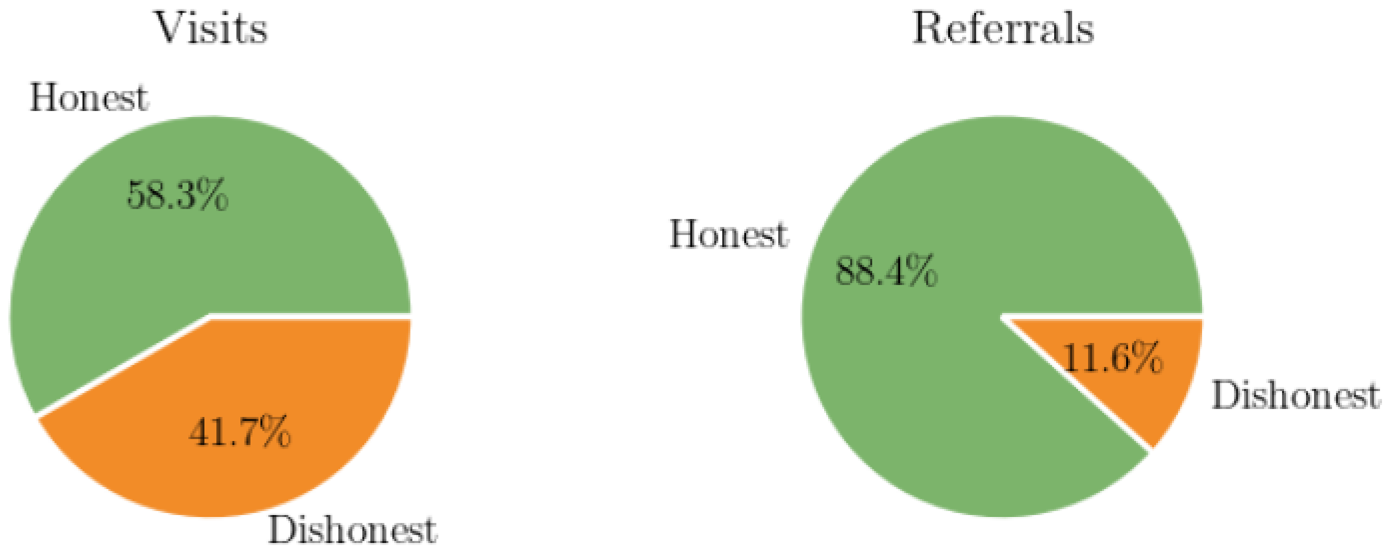


Lesson: Validating and enforcing user honesty should be a priority in future deployments.



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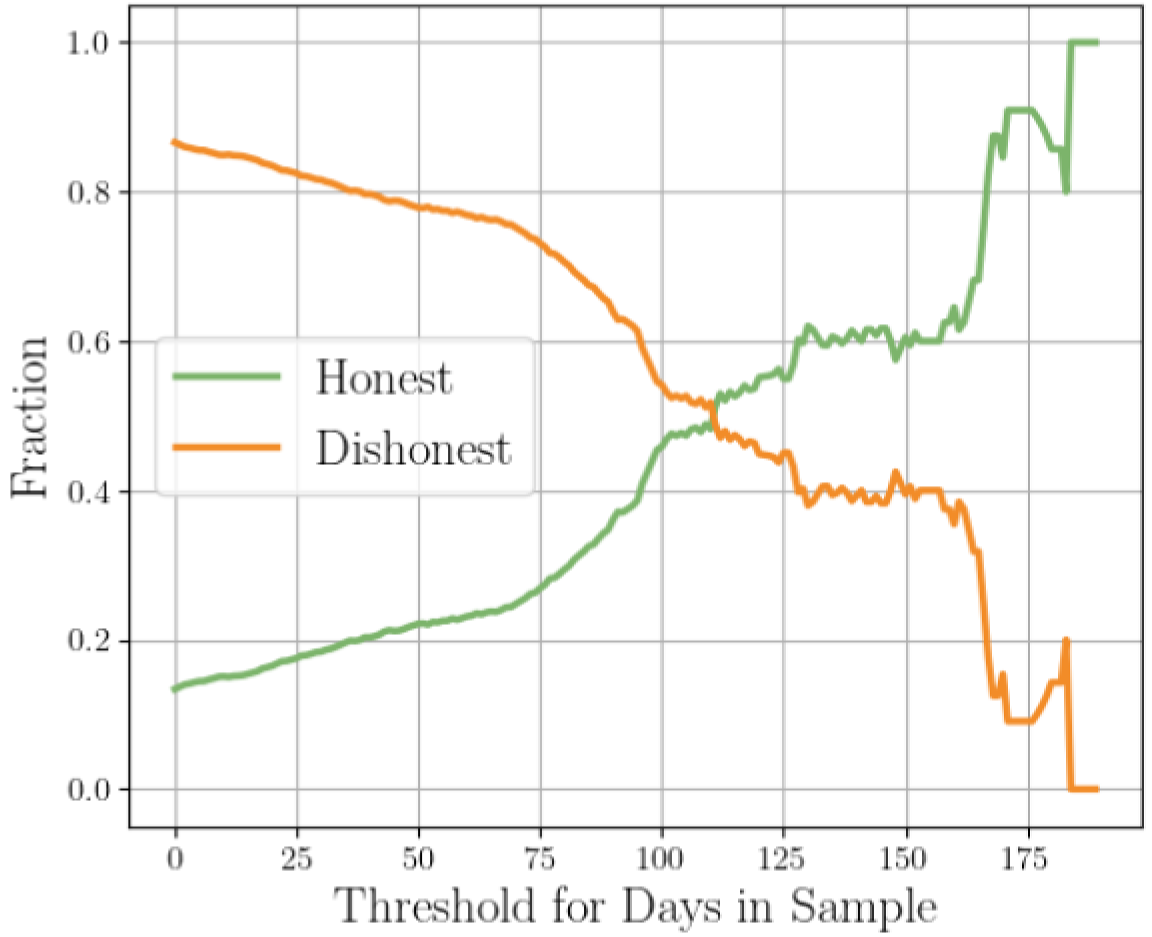

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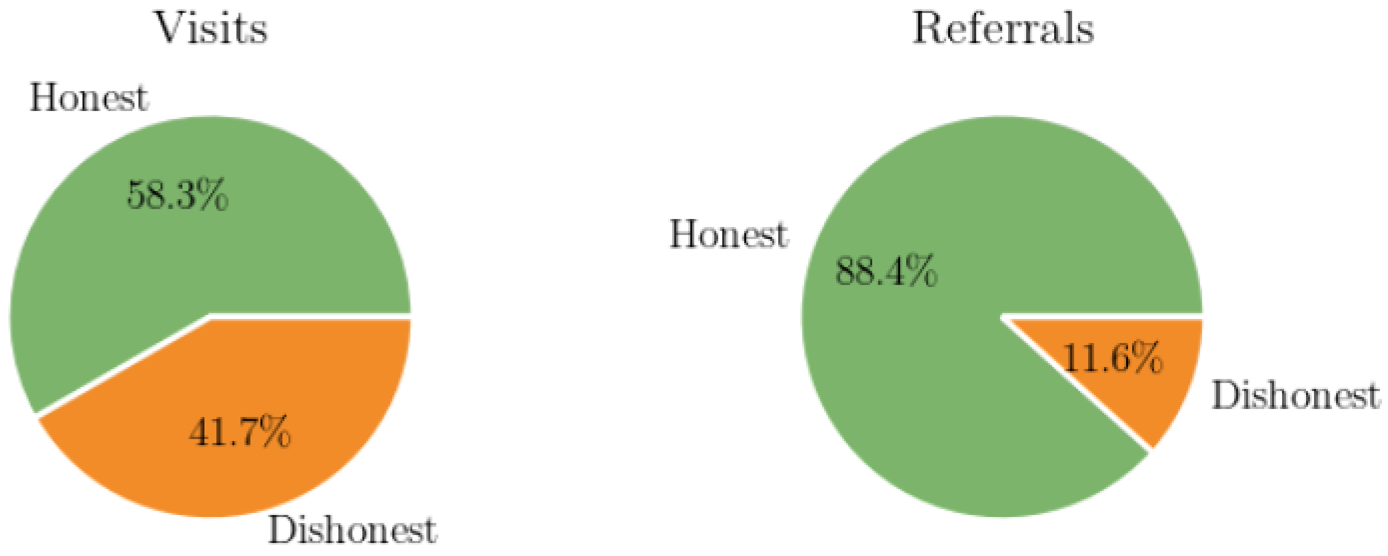
Lesson: Our learning process is surprisingly robust to dishonest users.



Strengthening the Threat Model

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- Reduce or eliminate trust in the core computation

Strengthening the Threat Model

- AWS as a single point of failure
- Reduce or eliminate trust in the core computation
- Anonymous payments

Thank You!

sambux@bu.edu